

PhD THESIS

Appraising the construct validity of Product Innovation Capability and identifying its association with Firm Performance through meta-analysis

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Innovation Capability and identifying its association
with Firm Performance through meta-analysis*

Sumeet Om Sharma

Bachelor of Engineering (Mechanical)

Master of Business Administration

A thesis submitted to the
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CONFERENCE PAPER ARISING FROM THE THESIS

A paper arising from the thesis Chapters-2 and 3, was presented at ANZAM 2013 held at Hobart, Tasmania, but was opted-out from publication in the Conference Proceedings.

Sharma S.O. (2013) "Towards a comprehensive operationalisation of dynamic capabilities: Gap identification in product innovation capability measurement models" presented to *Australia and New Zealand Academy of Management* (Authorship 100%)

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ABSTRACT

In the literature focused on dynamic capability and innovation constructs, a prominent theme is the identification and analysis of antecedents that drive firm performance. In particular, the dynamic capability construct of product innovation capability (PIC), and its implications for firm performance, has spurred substantial scholarly interest. This has eventuated into a considerable amount of theoretical and empirical literature on the PIC and firm performance relationship. The accumulation of empirical evidence on the PIC–firm performance relationship has attained a critical mass that warrants and enables a systematic synthesis of findings.

Notwithstanding the advancements made in understanding PIC, and its relationship with firm performance, several gaps and contradictions persist in the literature. For example, empirical findings concerning the relationship are often mixed, and theoretical contentions of Dynamic Capability (DC) Theory in general, have sometimes remained empirically unsubstantiated. The present study aims to advance DC Theory and innovation literatures by:

1. Undertaking a review of PIC measurement using theoretical triangulation, that entails a multi-theoretical appraisal of PIC construct validity.
2. Formulating an innovative meta-analytic methodology and conducting an investigation of the PIC–firm performance relationship and its moderation effects via a statistical synthesis of findings.

In undertaking a meta-analysis of the relationship between PIC and firm performance, the thesis firstly focuses on operationalisation of PIC in order to assess its construct validity as a dynamic capability construct. High construct validity of PIC is a necessary condition for enabling the development, empirical testing and application of DC Theory. Attaining high validity of PIC is also imperative for an assessment of its association with firm performance.

Since DC Theory is arguably still nascent, particularly in terms of its scant empirical validation, PIC construct validity assessment serves to consolidate the theoretical and empirical underpinnings of the theory. A critical gap is identified in PIC measurement models and a novel meta-analytic methodology for addressing the validity problem is developed and employed in the study.

The meta-analysis of the PIC–firm performance relationship aggregates 81 effect sizes (correlations), extracted from 57 studies, representing the magnitude and direction of this relationship. The synthesis enables the computation of a summary (cumulative) effect size for the relationship under investigation. The synthesis also offers insights into certain boundary conditions, under which the magnitude and/or direction of the focal relationship undergo a change. This is accomplished through *a priori* identification and sub-group analyses of potential moderator variables. By ascertaining the moderation effects concerning the PIC–firm performance relationship, DC Theory can also be better understood.

The meta-analytic results demonstrate a positive and strong association between PIC and firm performance, supporting the hypothesised relationship and yielding a point estimate for the true (i.e., construct-level) relationship. In other words, the current study provides a summary estimate of the actual underlying bivariate relationship of interest, by overcoming an identified construct validity problem that limits the existing PIC operationalisation methods. The validity problem in PIC, as determined through triangulation and relevant arguments, and the development of a unique meta-analytic model in this study, provide a broad spectrum of opportunities for further research.

CHAPTER ONE

INTRODUCTION

1.1. BACKGROUND FOR THE STUDY

Demystifying the antecedents of sustainable competitive advantage and consequent firm performance is a major aim of management research (Barney, 1991; Crook, Ketchen, Combs & Todd, 2008). Innovation has arguably been the most prominent subject of these research endeavours, for several decades (Damanpour & Aravind, 2012; Wolfe, 1994). Industry practitioners and researchers constantly strive to manage and investigate innovative activities (Artz, Norman, Hatfield & Cardinal, 2010; Marsh & Stock, 2003), including product innovation capability (PIC), as key determinants of firm performance. PIC enables the pursuit of critical success factors such as the introduction of innovative products that facilitate attainment of competitive advantage (O'Cass & Ngo, 2012; Porter, 1985; Verona, 1999).

Alongside the research focus on innovation, in their quest to answer the question of “why some organisations outperform others” (Crook et al., 2008: 1141), scholars have also directed substantial attention towards Dynamic Capability (DC) Theory. The theory has its genesis in the Resource Based View of the firm (Morgan, Vorhies & Mason, 2009; Schilke, 2014). DC Theory explains the rapid adjustments in organisational strategies/tactics that are necessitated by a constantly shifting business landscape (e.g., see Eisenhardt & Martin, 2000; Teece, Pisano & Shuen, 1997). The overarching applicability of DC Theory in explaining predictors of firm performance has led to its use in diverse fields, including (but not limited to) international business, marketing, operations management and entrepreneurship.

Dynamic capability is defined by Teece et al. (1997: 516) as “the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments”. As PIC is widely acknowledged as a

key dynamic capability, it can be considered as a focal point of convergence between DC Theory and innovation research (e.g., see O'Reilly & Tushman, 2008; Rosenbusch, Brinckmann & Bausch, 2011; Schilke, 2014).

Despite the popularity of DC Theory, it is still nascent and emerging (Di Stefano, Peteraf & Verona, 2010; Helfat & Peteraf, 2009). Several researchers contend that there remain research gaps that warrant attention for theoretical and empirical advancement (e.g., Barrales-Molina, Martínez-López & Gázquez-Abad, 2014; Vogel & Güttel, 2013; Zahra, Sapienza & Davidsson, 2006). Particularly, problems such as inconsistent measurement and conceptual vagueness of dynamic capabilities continue to persist (see Wang, Senaratne & Rafiq, 2015; Zheng, Zhang, Wu & Du, 2011).

The empirical investigation of the relationship between dynamic capabilities and firm performance has revealed inconsistent results. In particular, the relationship of PIC with firm performance is characterised by mixed findings, making it difficult to definitively determine if dynamic capabilities enhance firm performance (e.g., see Drnevich & Kriauciunas, 2011; Katila & Ahuja, 2002; Schilke, 2014). For example, several studies report a positive association between these constructs (e.g., Panayides, 2006; Tatikonda & Montoya-Weiss, 2001; Wolff and Pett, 2006), but a few also report a negative one (e.g., Katila & Ahuja, 2002; Penner-Hahn & Shaver, 2005). Such contradictory findings indicate that the theoretical contentions of DC Theory proponents, that higher levels of dynamic capabilities lead to superior firm performance, are not clearly supported (e.g., see Eisenhardt & Martin, 2000; Teece & Pisano, 1994).

Consequently, to gain insights into this pivotal relationship, a meta-analysis of empirical research that has accumulated on PIC–firm performance relationship is warranted. As meta-analyses generate summary estimates of the relationships of interest (Cooper, 2010; Hunter & Schmidt, 2004), a meta-analytic review of the PIC–firm performance link is undertaken in this research. Additionally, since researchers have recently underscored the urgent need for devising valid and reliable measures for dynamic capability constructs (Wang

et al., 2015), an appraisal of PIC construct measurement is undertaken using theoretical triangulation. The method of theoretical triangulation combines multiple theoretical frameworks to gain a superior understanding of the construct under investigation. Importantly, it has been demonstrated by researchers that triangulation enhances the construct validity of the variables of interest (e.g., see Halcomb & Andrew, 2005; Shih, 1998). Construct validity is “the degree of correspondence between constructs and their measures”, and it is “a necessary condition for theory development and testing” Peter (1981: 133). As the attainment of high construct validity is a pre-requisite for ensuring the expansion of substantive empirical literature (Cronbach, 1971; Nunnally, 1967), an assessment of PIC validity provides a foundation for conducting the meta-analysis.

1.2. RESEARCH GAPS AND AIMS

The central relationship in DC Theory that commands most attention in research is the one between dynamic capabilities and firm performance (Barreto, 2010). However, the empirical evidence of the relationship is conflicting not only in terms of magnitude but also direction (as highlighted in the previous Section-1.1). This inconsistency in findings leads to a degree of uncertainty with regards to the core relationship between dynamic capabilities and firm performance.

To better understand the relationship between PIC and firm performance, it is vital to gain a deeper understanding of PIC as a dynamic capability construct, and the extent to which its measures and conception correspond to each other. The present study aims to demonstrate that PIC measures are limited by a substantial measurement deficiency which also potentially influences other dynamic capability constructs. Due to the measurement deficiency of PIC in the literature, this study brings into focus the (lack of) construct validity in PIC measurement models. The construct validity problem of PIC is

revealed by theoretical triangulation and *a priori* contentions, which collectively facilitate an assessment of the degree of consistency between commonly used measures of PIC and its conception as a dynamic capability.

To address the operationalisation problem that causes PIC construct validity to be called into question, a unique meta-analytic model is presented in the thesis. The model seeks to provide a summary effect size (i.e., weighted correlation coefficient) as an estimate of the *true* relationship of interest, by accounting for the validity problem of PIC. Consequently, the proposed model maintains the focus of this research on construct-level relationship between PIC and firm performance. The use of the word *true* highlights the fact that meta-analyses aim to surmount primary study imperfections (e.g., sampling and measurement errors), thereby yielding accurate summary estimates of the relationships under investigation (Hunter & Schmidt, 2004; Schmidt & Hunter, 1996). The use of the word *true* also reflects the focus of meta-analyses on the population from which firm-samples are drawn and investigated in individual studies (Aguinis, Gottfredson & Wright, 2011). Thus, through a meta-analysis, the present study aims to resolve the contradictory findings of the PIC–firm performance relationship by determining an estimate of the strength and direction of the relationship. There has been no direct attempt to synthesise findings on the association of a prominent dynamic capability, such as PIC, with firm performance, and the current study fills this gap in DC Theory literature.

Furthermore, understanding the conditions under which a relationship changes in direction and/or magnitude is vital for theory development and testing (Viswesvaran & Ones, 1995). Thus, moderators of the PIC–firm performance relationship are also identified. Substantive (theory-derived) moderators identified are industry type, firm size and technological turbulence. These moderators have been a focal point of research in DC Theory and innovation literatures for various relationships under investigation (e.g., Damanpour, 1991; Rogers, 2004; Rubera & Kirca, 2012; Song, Droge, Hanvanich & Calantone, 2005). However, as boundary conditions of DC Theory remain vaguely defined and under-researched, the identification of

moderators and their effects on the PIC–firm performance relationship are of substantial importance (see Schilke, 2014; Wilhelm, Schlömer & Maurer, 2015).

The following research questions are formulated on the basis of identified gaps pertaining to the construct validity of PIC and a need for estimating the true PIC–firm performance relationship along with its boundary conditions.

Research questions:

1. *To what extent are PIC measures valid when examined using theoretical triangulation of complementary theories?*
2. *What is the magnitude and direction of the true (construct-level) relationship between PIC and firm performance?*
3. *Do industry type, firm size and technological turbulence moderate the relationship between PIC and firm performance?*

The research questions are predicated on understanding the focal relationship and delineating its boundary conditions, common to most meta-analyses in social sciences (see Aguinis et al., 2011; Hunter & Schmidt, 1990; 2004). The study investigates construct validity of PIC through theoretical triangulation that entails integration of DC, Organisational Ambidexterity and Process Management Theories. The central rationale of Organisational Ambidexterity (henceforth, referred to only as Ambidexterity) is that organisations have two broad mechanisms/strategies for learning that have been labelled exploitation and exploration (Atuahene-Gima & Murray, 2007; Baum, Li & Usher, 2000; Danneels, 2008; Levinthal & March, 1993). Process Management Theory, on the other hand, is focussed on process improvement and productivity (i.e., efficiency) enhancement (e.g., see Deming, 1986). Researchers have also emphasised the importance of Process Management Theory in examining innovation constructs (e.g., Busse & Wallenburg, 2011; Neely & Hii, 1998;

Wolfe, 1994). Importantly, PIC is frequently modelled as a process or as being embedded in processes in empirical research (Schilke, 2014). The *process-based* view of dynamic capabilities has emerged as a dominant paradigm in DC Theory (e.g., see Agarwal & Selen, 2009; Helfat, Finkelstein, Mitchell, Peteraf, Singh, Teece & Winter, 2007). Therefore, the current study adopts a process-based conception of PIC, and Process Management Theory is used in theoretical triangulation along with Ambidexterity and DC Theories.

The review of PIC measures through the lens of construct validity addresses the first research question by highlighting a deficiency that prevails in PIC measurement. The identification of the construct validity problem paves the way for devising an innovative methodology that underpins the PIC–firm performance meta-analysis undertaken in this research. The proposed meta-analytic methodology is centred on making adjustments to correlation coefficients (or simply, correlations), which are extracted from incorporated studies. The methodology is referred to as an *effect size weighting scheme* and it entails modifications to reported correlations. The correlations are the effect size metric in the current study and represent the direction and magnitude of the PIC–firm performance relationship. Hence, the two terms (i.e., correlation and effect size) are used interchangeably in the thesis.

Subsequently, the study synthesises empirical findings on the relationship of interest in order to directly address the second research question. The emphasis on true relationship reflects the primary aim of meta-analyses in attempting to determine construct-level associations (see Hunter & Schmidt, 2004). Substantive moderators potentially influencing the focal relationship are then identified and their moderation effects ascertained through sub-group analyses. Thus, determination of the boundary conditions of the PIC–firm performance relationship addresses the third research question.

1.3. SIGNIFICANCE AND JUSTIFICATION OF THE STUDY

The study contributes to the existing literature and knowledge base along multiple pathways as outlined in this Section.

First, by highlighting the construct validity problem of PIC, the study postulates a measurement approach that can guide empirical research in both DC Theory and innovation domains. By addressing the validity problem identified in this research, PIC can be measured more comprehensively, because constructs are captured adequately via the enhancement of their validity (see Cronbach, 1971; MacKenzie, Podsakoff & Jarvis, 2005; Nunnally, 1967; Nunnally & Bernstein, 1994). As already stated, the construct validity problem of PIC is identified using theoretical triangulation entailing a review of PIC measurement models and its conceptualisation as a dynamic capability. Discernment of the deficiency in PIC measurement is an important contribution of the thesis to DC Theory literature, as overcoming any gaps in construct operationalisation enables the development of valid measures (see Thorndike & Hagen, 1977). Consequently, empirical advancement of DC Theory can progress “beyond evidence of an *ad hoc* [emphasis in original] and piecemeal nature” (Wang et al., 2015: 28).

Triangulation also affords a greater level of clarity to the conception of PIC, thereby helping reduce the problem of conceptual vagueness in dynamic capability constructs (e.g., see Di Stefano et al., 2010; Peteraf, Di Stefano & Verona, 2013; Priem & Butler, 2001; Wilhelm et al., 2015; Williamson, 1999). In the specific context of the PIC–firm performance meta-analysis, the construct validity assessment is argued to be critical for substantively addressing the research questions of the thesis. This is because the greater the extent to which PIC measures are valid; the computed summary effect size would better estimate the true relationship of PIC with firm performance.

Second, the thesis presents an innovative meta-analytic methodology that entails modifications to reported effect sizes and seeks to overcome the

problem in PIC measurement. Development of the methodology is a salient contribution of this research as the formulation of such a method is unprecedented. Consequently, the thesis advances the applicability of meta-analyses by establishing a methodological procedure enabling *post hoc* (i.e., after findings have been reported and accumulated for synthesis) adjustments in reported effect sizes. The methodology enhances the validity of PIC, thereby yielding a superior summary effect size estimate of the PIC–firm performance relationship. The computed summary effect size represents the magnitude and direction of the relationship through aggregation of empirical findings (Lipsey & Wilson, 2001). The generation of a summary effect size will resolve the contradiction in research findings, thus clarifying the nature of the relationship under examination and making another contribution to DC Theory (e.g., see Drnevich & Kriauciunas, 2011; Schilke, 2014).

Third, the determination of potential moderation effects of the focal relationship by industry type, firm size and technological turbulence offers insights into the boundary conditions of DC Theory. Considering the centrality of market dynamism in DC Theory, the thesis also sheds light on its moderation impact on the relationship of interest (e.g. see Protogerou, Caloghirou & Lioukas, 2012; Schilke, 2014; Wilhelm et al., 2015). This is achieved by drawing inferences from the moderation effect of technological turbulence on the PIC–firm performance relationship as technological turbulence is treated as a proxy for the market dynamism construct, in addition to being a substantive moderator *per se*.

1.4. OVERVIEW OF RESEARCH METHODOLOGY

Two principal research methods deployed in the study are outlined here.

1.4.1. Theoretical triangulation

The method of theoretical triangulation is employed for reviewing the congruency between PIC conceptualisation and measurement. This method has been used by researchers to enhance construct validity in diverse fields of scientific enquiry (e.g., see Halcomb & Andrew, 2005; Shih, 1998). Triangulation generally facilitates a superior understanding of constructs (and their validity) than is possible with a single theory used in isolation (e.g., see Breitmayer, Ayres & Knafl, 1993; Shih, 1998). Laying emphasis on the benefits of triangulation, Halcomb and Andrew (2005: 73) assert that “the triangulated approach provides a completeness of understanding of the concept under investigation”. Specifically, the importance of examining innovation constructs from multiple theoretical viewpoints is underscored in the literature (e.g., see Abrahamson, 1991; Poole & Van de Ven, 1989; Wolfe, 1994).

For undertaking triangulation, fundamentals of DC, Process Management and Ambidexterity Theories are used in the research. Ambidexterity is employed as there are similarities identified between DC Theory and Ambidexterity by researchers (e.g., O'Reilly & Tushman, 2008; Vogel & Güttel, 2013). Inclusion of Process Management in triangulation is justified on the grounds that a process-based view of PIC is explicitly subscribed to in the thesis. Subsequent to a construct validity appraisal of PIC, empirical findings are statistically synthesised using a meta-analytic review to determine the nature of the PIC–firm performance relationship and its boundary conditions, as explained below.

1.4.2. Meta-analysis

Meta-analyses incorporate statistical techniques for combining independently reported findings through robust procedures (Brinckmann, Grichnik & Kapsa, 2010; Cooper, 2010; Lipsey & Wilson, 2001). Meta-analyses generate useful and practical knowledge through the integration of empirical findings that individual studies are often unable to provide in isolation (Hunter, Schmidt &

Jackson, 1982). Generally, they enable the testing of hypothesised bivariate relationships by correcting for errors due to sampling and measurement (Crook et al., 2008; Hunter & Schmidt, 2004).

Meta-analyses largely gained popularity due to the recognition of the limitations of qualitative narrative reviews (see Hunter et al., 1982), and a need for statistical rigour in the synthesis of empirical findings (see Glass, 1976). Their application in social science research is growing steadily as evidenced by an increasing number of meta-analytic reviews being published in academic journals (see Aguinis et al., 2011).

Additionally, meta-analyses provide insights into moderator variables that may account for variations in the relationship of interest, thereby assisting researchers in theory development and testing (Viswesvaran & Ones, 1995). The ability to assess moderation effects is a pivotal strength of meta-analyses over narrative reviews (Aguinis et al., 2011).

The current research endeavours to expand the applicability of meta-analyses by demonstrating how construct validity gaps can be bridged by overcoming operationalisation deficiencies. By making adjustments to effect sizes, the study offers a better understanding of the true PIC–firm performance relationship and its moderation effects.

1.5. DEFINITIONS OF KEY CONSTRUCTS

Due to the diversity of concepts employed in the thesis and their varied use in the literature, Table 1.1 lists the definitions of central constructs (in alphabetical order).

Table 1.1: Definitions of the central constructs employed in the thesis

Constructs	Definitions
Dynamic capability	“the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” Teece et al. (1997: 516)
Environmental/Market dynamism	“the amount and unpredictability of change in customer tastes, production or service technologies, and the modes of competition in the firm's principal industries” Miller and Friesen (1983: 233)
Meta-analysis	a set of quantitative techniques used "in solving the general problem of integrating findings across studies to produce some cumulative knowledge" Hunter et al. (1982: 137)
Product Innovation Capability (PIC)	“routines and processes firms have in place for undertaking innovation related activities in areas such as developing new products, extending product ranges, improving existing product quality, improving production flexibility and exploiting the most up-to-date technologies” O’Cass and Ngo (2012: 125)
Technological Turbulence	“the rate of technological change” Jaworski and Kohli (1993: 57)
Triangulation	“the combination of two or more theories, data sources, methods, or investigators in one study of a single phenomenon” (Shih, 1998: 632)

Additionally, Appendix-1 presents a glossary of acronyms/abbreviations used in the thesis. The definitions of other terms which are listed in this Appendix are explained as they appear in the text of the thesis.

1.6. SCOPE OF THE STUDY

The research is confined within certain delimitations in terms of its scope, which are outlined here.

Notwithstanding sustainable competitive advantage being a core construct in the strategic management literature including DC Theory (see Barreto, 2010; Grant, 1996b; Teece, 2009), its operationalisation is generally not undertaken. According to Weerawardena and O'Cass (2004), competitive advantage refers to the attainment of a position by a firm that confers superiority upon it in its market and financial positions, which along with the competitive strategy of the firm, is immune to duplication by competitors. As affirmed by Crook et al. (2008: 1152) that "competitive advantage is difficult to measure, and its direct assessment is seldom attempted". Therefore, as competitive advantage does not render itself to robust and reliable measurement (Ketchen, Hult & Slater, 2007), the measures of actual firm performance are usually deployed as a proxy for quantifying competitive advantage (Barney & Arkan, 2001). The underlying premise here is that superior performance is a reflection of competitive advantage (Crook et al., 2008), thereby justifying the use of performance metrics to operationalise competitive advantage. Thus, rather than competitive advantage, the current study employs firm performance (with measures such as sales/market growth and return on assets) as the dependent variable. This is also necessary given the use of meta-analysis (as a methodology) in the current study, as the empirical studies make use of firm performance rather than competitive advantage (e.g., see Crook et al., 2008; Krasnikov & Jayachandran, 2008).

Amongst the studies incorporated in the meta-analysis, very few are longitudinal, with most being cross-sectional in nature. This distinction in research design is important in that it bears on the extent of confidence that can be placed in inferring causality between the dependent and independent variables (see Forza, 2002; Van de Ven & Huber, 1990; Ware, 1985). Causality between the variables can be inferred with longitudinal designs but such an inference is not justifiable with cross-sectional designs (Forza, 2002). Thus, in the context of the current meta-analytic review, conclusive inferences about PIC and firm performance causality should be drawn with caution due to incorporated studies being mostly cross-sectional.

Additionally, the study investigates the presence of potential moderators that are identified theoretically. Examination of empirical moderators, such as

study characteristics, that may also moderate the relationship of interest are not included in the meta-analysis (e.g., see Rosenbusch et al., 2011). This is primarily because the latter (empirical) moderators are not theory-derived *per se*, but consequent to research design and operationalisation choices made by researchers.

1.7. THESIS STRUCTURE

The thesis is structured into six Chapters and an overview of the research is provided in this introductory Chapter.

Chapter-2 presents a literature critique that entails theoretical triangulation between DC, Ambidexterity and Process Management Theories. The triangulation and *a priori* arguments enable the identification of a gap in PIC operationalisation. Additionally, a review of innovation literature will highlight inconsistencies that have persisted in empirical research. The Chapter also reviews meta-analytic studies conducted on innovation-focussed constructs (e.g., R&D capability) and firm performance as independent and dependent variables, respectively.

Chapter-3 describes a methodology (labelled weighting scheme) that aims to overcome the validity problem of PIC by undertaking adjustments to reported effect sizes. Based on theoretical rationales, the Chapter also proposes moderator variables that are expected to impact the relationship under investigation.

Chapter-4 presents the design and methodological framework employed in the study. The framework chiefly concerns: 1. a computational protocol for the weighting scheme and 2. conventional meta-analytic procedures that include study coding, summary effect size computation, moderation and sensitivity analyses, and assessment of the file drawer problem.

Chapter-5 presents a summary of the dataset, heterogeneity analysis, as well as the core findings of the meta-analysis including summary effect size, moderation and sensitivity analyses, and file drawer analysis.

Chapter-6 presents a discussion of the findings in terms of research questions and hypotheses. Discussions of the implications of this research for theory and practice, and potential limitations are also presented. The Chapter concludes with prospects for future research.

1.8. CHAPTER SUMMARY

The current research is conducted in order to shed light on the true PIC–firm performance relationship, and models PIC as a dynamic capability. The thesis presents a quantitative review and empirical generalisation of the relationship under investigation through a meta-analysis that is underpinned by a triangulation of three prominent theories. The thesis aims to expand the present state of knowledge concerning a prominent dynamic capability construct (i.e., PIC), the relationship between PIC and firm performance, and the impact of relevant moderator variables on the relationship. In addition, the presentation of an unprecedented methodological procedure in the thesis significantly increases the scope for the application of meta-analyses.

CHAPTER TWO

REVIEW OF LITERATURE

2.1. INTRODUCTION

In the research centred on examining the antecedents of firm performance, innovation is arguably the most extensively investigated subject (Jiménez-Jiménez & Sanz-Valle, 2011; Merrilees, Rundle-Thiele & Lye, 2011; Rubera & Kirca, 2012). Researchers contend that innovation is critical for keeping pace with shifts in the business environment (e.g., Kim & Maubourgne, 2005; Schumpeter, 1934; Slater, Mohr & Sengupta, 2014; Thornhill, 2006). Within innovation literature, product innovation commands a high level of scholarly attention (Ar & Baki, 2011; Artz, Norman, Hatfield & Cardinal, 2010; Delgado-Verde, Castro & Navas-Lopez, 2011).

Innovation capability as a determinant of innovation outcomes is asserted by researchers as a very potent driver of firm performance (e.g., Hooley, Greenly, Cadogan & Fahy, 2005; Hult, Hurley & Knight, 2004; Hurley & Hult, 1998; Merrilees et al., 2011; Porter, 1990; Schumpeter, 1934; Weerawardena & O'Cass, 2004). Innovation capability has been subjected to examination in diverse contexts such as small and medium enterprises (SMEs), business-to-business and emerging economies (e.g., see Branzei & Vertinsky, 2006; Calantone, Cavusgil & Zhao, 2002; Merrilees et al., 2011; O'Cass & Ngo, 2012; O'Cass & Sok, 2013a; 2013b; Sok & O'Cass, 2011; Thornhill, 2006; Wong & Merrilees, 2005).

Research also indicates that dynamic capabilities perform a central role in facilitating innovation as a means to attaining superior performance levels (e.g., see Lawson & Samson, 2001; Levinthal, 2000; Lichtenthaler & Muethel, 2012; Menguc & Auh, 2006; Teece, 2007; Teece, 2009; Teece & Pisano, 1994; Zollo & Winter, 2002). Considering the research interest in investigating

the capacity of organisations for adapting to environmental changes (Benner, 2009), explaining the role of dynamic capabilities under shifting environmental conditions has emerged as a focal point of attention (e.g., see Drnevich & Kriauciunas, 2011; Schilke, 2014). In essence, DC Theory seeks to provide answers to fundamental questions such as, how do routines and processes stimulate organisational change and adaptation, thereby enabling a firm to remain in sync with the environmental shifts, and outperform rivals.

Researchers acknowledge PIC to be a key dynamic capability (e.g., Barrales-Molina et al., 2014; Eisenhardt & Martin, 2000; O'Reilly & Tushman, 2008; Rosenbusch et al., 2011; Schilke, 2014). PIC is a very prominent research construct as it is at the crossroads of multiple interconnected streams, such as DC Theory, innovation, Ambidexterity, knowledge management and organisational adaptability (e.g., see Cepeda & Vera, 2007; López, 2005; Vogel & Güttel, 2013). As innovation encompasses the introduction of new products, PIC is deemed a subset of the overarching innovation capability construct in this thesis (see Calantone et al., 2002; Oke, Burke & Myers, 2007; Zhang, Garrett-Jones & Szeto, 2013). O'Cass and Ngo (2012) define PIC as routines or processes embedded in firms that enable the pursuit of critical success factors such as new product development, re-engineering of production and distribution mechanisms and deployment of latest technologies. This definition of PIC as provided by O'Cass and Ngo (2012) is the one chosen for the current research as it attempts to encapsulate the multidimensional essence of PIC. The chosen definition is largely reflective of PIC's conception as a dynamic capability construct. Given the significance accorded by researchers on dynamic capabilities and innovation in enhancing firm performance, PIC can be asserted to be a key determinant of performance.

This Chapter reviews the literature on innovation and dynamic capabilities (PIC in particular), and the association of PIC with firm performance, with the latter (i.e., the focal relationship) primarily from the DC Theory perspective. The Chapter commences with a theoretical triangulation between DC, Ambidexterity and Process Management Theories to gain insights into the

multidimensional nature of PIC. Complementarities identified amongst the three theories are then deployed as a lens to review the conception and operationalisation of PIC, in order to gain insights into its construct validity.

Underpinned by triangulation, a review of relevant and overlapping innovation constructs is also undertaken. The PIC–firm performance relationship is subsequently outlined and reviewed in relation to market dynamism, as a potential moderator of the relationship of interest (see Schilke, 2014). The Chapter concludes with a content analysis of meta-analyses recently conducted, that investigate the firm performance implications of several innovation-focussed and capability constructs. The content analysis is undertaken in order to establish an imperative for a meta-analytic review on the PIC–firm performance relationship.

2.2. DC, AMBIDEXTERITY AND PROCESS

MANAGEMENT THEORIES: A TRIANGULATION

The emergence of DC Theory has followed an evolutionary trajectory and does not owe its origins to any single moment of truth. However, seminal articles such as Teece and Pisano (1994), Teece et al. (1997), Eisenhardt and Martin (2000), and Makadok (2001), published in the last two decades, have contributed immensely in systematically organising and popularising DC Theory. Notwithstanding the growth and promise of the theory, it is still nascent and undergoing consolidation (Di Stefano et al., 2010; Helfat & Peteraf, 2009). Refinements of core constructs of the theory and empirical investigations are facilitating further advancements (Barrales-Molina et al., 2014). This offers substantial opportunities for further research in the realm of DC Theory.

The literature ascribes a competitive advantage-creating characteristic to dynamic capabilities under changing environmental conditions (e.g., Eisenhardt & Martin, 2000; Grant, 1996b; Makadok, 2001; Rosenbusch et al., 2011; Wilhelm et al., 2015). The attainment of competitive advantage is said

to enable a firm to achieve superior performance levels (see Barney, 1991; Newbert, 2007; Porter, 1985). DC Theory emphasises the pivotal contribution of dynamic capabilities in the attainment of competitive advantage and consequent performance through the reconfiguration and redeployment of resources owned and controlled by the focal firm (e.g., Barreto, 2010; Teece et al., 1997). The performance-enhancing characteristic of dynamic capabilities is underscored by a statement made by Zollo and Winter (2002: 341) that “both superiority and viability will prove transient for an organization that has no dynamic capabilities.” In a similar vein, Teece (2007: 1320) affirms that “dynamic capabilities lie at the core of enterprise success (and failure).”

The agreement in the research community regarding the ability of dynamic capabilities to enhance firm performance arguably stems from the conception of and *a priori* deductions concerning the dynamic capability construct. As the conception of dynamic capabilities is largely based on organisational adaptation, learning and knowledge creation (e.g., see Denford, 2013); their contribution to firm performance becomes mostly self-evident. Thus, the dynamic capability construct has also come under criticism by some researchers who claim that conceptions of dynamic capabilities are tautological and vague (e.g., Priem & Butler, 2001, Williamson, 1999). Further research such as the present study, can potentially aid in overcoming such criticisms surrounding DC Theory.

To identify the constituents of dynamic capabilities, a group of scholars argue that dynamic capabilities are collective manifestations of micro-level factors such as individual-level cognitions and interactions, memory systems and other micro-processes that are together referred to as micro-foundations (e.g., Argote & Ren, 2012; Felin, Foss, Heimeriks & Madson, 2012; Teece, 2007). This viewpoint is an emergent field within DC Theory (Helfat & Peteraf, 2014), and explains the creation and enhancement of dynamic capabilities from micro-foundational level. On the other hand, the conventional and (hitherto) mainstream paradigm conceptualises dynamic capabilities at firm- and functional-level (e.g., see Barrales-Molina et al., 2014; Danneels, 2012; Drnevich & Kriauciunas, 2011). There is support for both perspectives and

they approach the theoretical conception of capabilities at different levels; therefore they are not contradictory but appear complementary. Empirical literature is predominantly focussed on the latter view (i.e., firm-level) and owing to the nature and scope of the current study (i.e., being a meta-analytic review), it is the firm-level conceptualisation of dynamic capabilities that is employed. The preceding description of the two distinct (yet complementary) streams of DC Theory research assumes importance for understanding the level of analysis at which the present study operates (for a detailed discussion, see Forza, 2002).

Dynamic capabilities are argued by several researchers to have a broad role that encompasses opportunity seeking and seizing on one end, to productivity enhancement on the other (e.g., see Agarwal & Selen, 2009; Benner & Tushman, 2003; Ghemawat & Costa, 1993; O'Reilly & Tushman, 2008). Makadok (2001: 389) highlights the productivity-enhancing function of dynamic capabilities by asserting that “the primary purpose of a capability is to enhance the productivity of other resources that the firm possess”. The overarching role attributed to the dynamic capability construct also highlights its multidimensionality (see Agarwal & Selen, 2009; Barreto, 2010).

With the development of DC Theory in the last two decades, there has been a simultaneous development of Ambidexterity Theory with a seminal publication by March (1991). A group of researchers maintain that DC Theory and Ambidexterity exhibit overlaps and complementarities (see Benner & Tushman, 2003; Danneels, 2008; Day, 2011; Ghemawat & Costa, 1993; O'Reilly & Tushman, 2008). Such comparisons between the two theories warrant a review of overlaps, as such an analysis can facilitate a superior understanding of PIC and its operationalisation. Thus, a review of DC Theory and Ambidexterity is presented next. This review of overlaps between the two theories (DC and Ambidexterity) is the first step of theoretical triangulation.

2.2.1. Overlaps between DC and Ambidexterity Theories

The central rationale of Ambidexterity is that organisations have two broad mechanisms/strategies for learning that have been labelled Exploitation and Exploration (e.g., Atuahene-Gima & Murray, 2007; Baum et al., 2000; Danneels, 2008; Levinthal & March, 1993; March, 1991; Raisch & Birkinshaw, 2008). Exploitative mechanisms revolve around the fine-tuning and optimisation of existing resources and capabilities (Lubatkin, Simsek, Ling, Veiga, 2006; Sirén, Kohtamäki & Kuckertz, 2012), whereas exploratory mechanisms are centred on augmenting new resources and capabilities to develop a broader set of diverse functional activities (Danneels, 2002; 2008; Uotila, Maula, Keil & Zahra, 2009). Broadly, exploitative learning and related organisational activities aim at the enhancement of productivity and predictability of existing routines and outcomes. Therefore, organisational objectives are attained through exploitative activities that encompass a diverse range of initiatives, such as Total Quality Management, Six Sigma and Benchmarking (Day, 2011), that primarily serve to enhance organisational efficiency. By contrast, the aim of exploratory activities is achieved through active experimentation, risk taking and flexibility (Day, 2011), which principally improve the effectiveness of firms. From the Ambidexterity standpoint, Danneels (2008) and Day (2011) propose that capabilities function either to enable exploitation of resources possessed by the firm, or to facilitate effective exploration and seizure of new opportunities. It is chiefly the latter function (i.e., exploration and opportunities seizing) that has been ascribed to dynamic capabilities (e.g., PIC) by them. The former function (i.e., exploitation of resources) has mostly been attributed to operational capabilities by these researchers.

A somewhat different viewpoint is proposed by another group of researchers who assert that dynamic capabilities perform an overarching function encompassing both exploitative and exploratory activities (e.g., Benner & Tushman, 2003; Ghemawat & Costa, 1993; O'Reilly & Tushman, 2008). Benner and Tushman (2003: 238) affirm that “dynamic capabilities are rooted in both exploitative and exploratory activities”. In a similar line of reasoning,

and endorsing the comprehensive functionality attributed to dynamic capabilities, O'Reilly and Tushman (2008) demonstrate substantial overlaps between DC Theory and Ambidexterity. They maintain that dynamic capabilities cover a broad spectrum of activities from exploration to exploitation, and they arrive at this conclusion through a systematic comparison of fundamental tenets of DC Theory and Ambidexterity. O'Reilly and Tushman (2008: 190, 185) further highlight that “dynamic capabilities are at the heart of the ability of a business to be ambidextrous—to compete simultaneously in both mature and emerging markets—to explore and exploit”; and that “ambidexterity acts as a dynamic capability”. Similar arguments about dynamic capabilities residing at the core of both exploratory and exploitative innovations are underscored by other scholars (e.g., Ancona, Goodman, Lawrence & Tushman, 2001; Raisch & Birkinshaw, 2008; Schreyoegg & Kliesch-Eberl, 2007; Tushman & O'Reilly, 1996). A bibliometric review by Vogel and Güttel (2013) has identified Ambidexterity as a field of research within DC Theory, thereby providing further evidence that overlaps between DC and Ambidexterity Theories are now well established and recognised in the research community. In light of the preceding discussion, it is contended that accounting for both exploitative and exploratory functions is vital for PIC operationalisation.

Makadok (2001) emphasises that capabilities (in general) are created for the primary purpose of productively utilising the other resources with which a firm is endowed. This contention further highlights the resource productivity-enhancing characteristic of dynamic capabilities, in addition to their key role in facilitating exploration. Additionally, researchers opine that the conception and development of operational capabilities (that drive exploitative activities) are enabled by dynamic capabilities (e.g., see Danneels, 2008; Day, 2011; Drnevich & Kriauciunas, 2011; Helfat & Peteraf, 2003; Teece et al., 1997; Winter, 2003; Zahra et al., 2006). This implies that organisational outputs and performance are also indirectly driven by dynamic capabilities (Cepeda & Vera, 2007; Helfat & Peteraf, 2003; Protogerou et al., 2012), via creation of operational capabilities. These assertions also underpin the contention that dynamic capabilities (e.g., PIC) play an overarching role in both exploration

and exploitation, with the latter being driven both directly and indirectly (via creation of operational capabilities) by dynamic capabilities.

The broad applicability of DC Theory is underscored by Eisenhardt and Martin (2000) in their influential paper, as they maintain that the empirical research on dynamic capabilities extends well beyond the realm of the Resource Based View (RBV) of the firm. They state that “dynamic capabilities actually consist of identifiable and specific routines that often have been the subject of extensive empirical research in their own right outside of RBV” (Eisenhardt & Martin, 2000: 1107). Several specific examples of dynamic capabilities, such as that of product development processes and knowledge creation processes have been cited by them to contend that dynamic capabilities have been empirically investigated extensively, even if not explicitly recognised within the RBV and DC Theory frameworks. This is an important observation as it justifies the inclusion of studies in the current meta-analysis to those that are not explicitly conducted within the RBV and DC Theory frameworks, in order to enhance the statistical power of the meta-analysis.

Underpinned by the exploitation dimension of PIC, it is argued that the measurement models of PIC must include the dimension concerning the efficiency of resource utilisation. Therefore, the PIC measurement models must contain measures that enable evaluation of the degree of productivity with which resources are leveraged for producing product innovation outcomes. It is concluded that the complementarities amongst DC and Ambidexterity Theories clearly point to an imperative for PIC measurement models to operationalise the construct from both exploratory and exploitative standpoints.

Dynamic capabilities are frequently conceptualised by DC Theory proponents as processes (e.g., Eisenhardt & Martin, 2000; Teece et al., 1997), and recent empirical research on dynamic capabilities has adopted this view (e.g., see Li & Liu, 2014; Schilke, 2014). Owing to the process-based conception of the dynamic capability construct, PIC will now be discussed in the context of Process Management Theory. The overview of overlaps between DC and

Process Management Theories is the subsequent step in theoretical triangulation.

2.2.2. DC and Process Management Theories

Process Management is centred on process mapping, improvement and adherence to improved organisational systems (Benner & Tushman, 2003), and has overarching applicability in diverse areas (Bergman & Klefsjo, 1990; Ravichandran & Rai, 1999). Process Management paved the way for quality and productivity programs such as Total Quality Management (Hackman & Wageman, 1995), in addition to Business Process Re-engineering, Statistical Quality Control and Six Sigma (see Benner & Tushman, 2002). In essence, Process Management is largely focussed on process improvement and efficiency enhancement. The recurrent theme of process efficiency and improvement is the productivity with which resources are utilised (Ravichandran & Rai, 1999). Thus, it can be contended that the emphasis placed on resource productivity maximisation in Process Management largely corresponds with resource exploitation and resource leveraging dimensions of Ambidexterity and dynamic capabilities respectively.

Helfat et al. (2007) highlight the ever-increasing popularity amongst researchers of a process-based conceptualisation of dynamic capabilities, and PIC is frequently modelled as processes (e.g., see Eisenhardt & Martin, 2000; Li & Liu, 2014; O'Cass & Ngo, 2012; Schilke, 2014). The process-based conceptualisation is critical for facilitating empirical investigation of dynamic capabilities (Schilke, 2014). Importantly, research on dynamic capabilities has demonstrated the benefits of applying Process Management in the area of new product development (e.g., see Benner, 2009; Garvin, 1995; Harry & Schroeder, 2000). Consequently, the conception of PIC as a process warrants an examination from the lens of Process Management (Benner & Tushman, 2003).

A large number of researchers also conceptualise innovation as a *process* (e.g., Alam, 2011; Busse & Wallenburg, 2011; Nelson, 1993; Noor & Pitt, 2009; Poole & Van de Ven, 1989; Rosenbusch et al., 2011). The importance and applicability of Process Management in examining innovation has been highlighted as being an integral component of innovation literature (e.g., see Busse & Wallenburg, 2011; Neely & Hii, 1998; Wolfe, 1994). Labelled Process Theory Research, the integration of Process Management with innovation considers discrete and identifiable innovative processes as the subjects of investigation (Busse & Wallenburg, 2011; Wolfe, 1994). Such research has however been largely confined to the examination of innovation in specific fields, such as supply chain management and manufacturing in which the application of Process Management yielded substantial efficiency gains, with well documented benefits (e.g., see Deming, 1986).

In the context of product development processes, proponents of Process Management have asserted the imperative of deploying Process Management for not only enhancing product quality but, equally importantly, to improve the efficiency of product development processes (e.g., Crosby, 1979; Deming, 1986). Similarly, Ravichandran and Rai (1999) opine that process efficiency is of paramount importance to firms as the productivity of organisational processes strongly influences operating costs such as the cost of production, delivery and servicing of products.

Notwithstanding the potential of Process Management, it has not been applied in all research fields that could benefit from its application, as evidenced by the relatively few publications focussing on Process Management in DC Theory and innovation literature. The scant attention given to Process Management in innovation and dynamic capability research has been underscored by researchers. For example, Benner (2009) contends that the potential of Process Management in research efforts focussing on organisational routines and change has not been sufficiently tapped. In a similar vein, Benner and Tushman (2003: 246) highlight the need for greater research efforts to integrate Process Management with DC Theory and innovation literatures, and state that:

Through process management practices, an organization becomes increasingly skilled at producing outputs that leverage existing knowledge about inputs, technologies, manufacturing techniques, or distribution channels. New innovations that further utilize these capabilities will benefit from these efficiencies and lend themselves to even more measurable success.

Considering the importance of applying Process Management to constructs modelled as processes (such as PIC), the sporadic integration of Process Management with DC Theory and innovation points to a deficiency in the literature. Hence, research efforts (as the current study) directed towards integration of Process Management and DC Theory can provide useful insights into the nature of dynamic capability constructs and their operationalisation. The preceding theoretical triangulation informs the conception and operationalisation of PIC in the current study.

The following discussion reviews PIC conception and the measurement models commonly adopted in the literature. This will be presented in the context of theoretical triangulation between DC, Process Management and Ambidexterity Theories, and their common focus on the efficient utilisation of resources. The investigation of PIC operationalisation as a dynamic capability is undertaken to ascertain the degree of correspondence between its measures and theoretical conception.

2.3. CONCEPTUALISATION AND MEASUREMENT OF PIC: OVERLAPPING CONSTRUCTS AND MULTIDIMENSIONALITY

An examination of the degree to which the conception and operationalisation of PIC are congruent, paves the way for the development of a measurement model that comprehensively assesses PIC (see Mackenzie et al., 2005). Since dynamic capability is a multidimensional construct (Barreto, 2010), a multi-pronged operationalisation of PIC is needed. O'Cass and Ngo (2012) operationalise PIC using measures that encompass product and process innovation, expansion of product range, product quality improvement and

application of advanced technology. Identical or semantically similar measures are used in other studies investigating PIC (e.g., Delgado-Verde et al., 2011; Grawe, Chen & Daugherty, 2009; O'Cass & Sok, 2013b), and also in studies operationalising the broader innovation capability construct (e.g., Adler & Shenbar, 1990; Calantone et al., 2002; Guan & Ma, 2003; Hurley & Hult, 1998; Panayides, 2006). Due to the commonalities observed in the operationalisation of PIC and some other innovation constructs on one hand, and certain inconsistencies in the literature on the other, a few prominent innovation-focussed constructs are outlined next. The following review serves to identify a few sources of inconsistencies and also determine whether studies investigating relationships between firm performance and innovation constructs (that overlap with PIC), are suitable to be included in the current meta-analysis.

2.3.1. Overlapping constructs and inconsistencies

Innovativeness is often conceptualised and operationalised in a very similar way to innovation capability (e.g., see Calantone et al., 2002; Hult et al., 2004; Panayides, 2006), and the two constructs are sometimes used interchangeably (e.g., Calantone et al., 2002). Panayides (2006: 466) states that “a key factor in the success of firms is the extent of their innovation capability also referred to in the literature as innovativeness”. Similarly, a few studies employ terms innovation and innovativeness interchangeably (e.g., Damanpour, 1992; Ettlie & Rubenstein, 1987). However, other studies define innovativeness as the openness and propensity to embrace fresh ideas, as distinct from innovation (e.g., Hurley & Hult, 1998; Menguc & Auh, 2006; Rubera & Kirca, 2012). This creates a degree of vagueness in the terminology and conceptualisations of constructs.

Some authors define and operationalise constructs identically but choose to label them differently in separate publications. For example, two studies published by Li and Atuahene-Gima (2001; 2002), operationalise constructs labelled product innovation strategy (in 2001) and product innovation (in 2002). However, no difference whatsoever can be detected between the metrics deployed to measure the two differently labelled constructs. Product

innovation strategy is defined by these authors in 2001 while no definition is provided for product innovation in the subsequent publication, with the two papers analysing the same firm sample. The complete lack of differentiation in measures of different constructs in these studies (investigating the same firm sample) highlights the ambiguity in definitions and measures prevailing in the innovation literature.

The study by Aragon-Correa, Garcia-Morales and Cordon-Pozo (2007) adopts an innovation definition as prescribed by the Product Development and Management Association (PDMA, 2004). However, explication of the innovation construct in the framework and hypotheses Section of the publication is not entirely congruent with the PDMA definition. Although, innovation is not described by PDMA as a capability, rather as an act and/or outcome of innovative efforts, the hypothesis Section refers to the construct as a capability, causing doubt about the essence of the construct as used in the study.

A more common deficiency in the literature is that several studies do not provide definitions of the innovation constructs used, such as innovativeness (e.g., see Durmuşoğlu & Barczak, 2011; Molina-Castillo & Munuera-Aleman, 2009; Salomo, Talke & Strecker, 2008). The absence of construct definitions compels the reader to make judgements and subjective interpretations that could be misleading. The inconsistencies highlighted here serve to demonstrate the level of discrepancy with regards to the terminology used, and the frequent mismatch between the conception and operationalisation of innovation constructs. This lack of correspondence in the conception and operationalisation of constructs often labelled identically; and conversely, the congruency in conception and operationalisation of constructs labelled differently, is acknowledged by many researchers (see Camisón & Villar-López, 2014; Damanpour & Aravind, 2012; Rubera & Kirca, 2012; Wolfe, 1994). Garcia and Calantone (2002) contend that many innovation studies are merely repetitions of prior research with constructs labelled differently and offer very little in terms of practical insights to industry practitioners. Similarly, Neely and Hii (1998) have highlighted the need for ensuring consistency in innovation terminology, and Wolfe (1994: 405) somewhat paradoxically

affirms that “the most *consistent* theme found in the organizational innovation literature is that its research results have been *inconsistent* [emphases in original]”. The inconsistencies discussed here inform the PIC–firm performance meta-analysis, as undertaken in the present research. Hence, prospective studies for incorporation in the meta-analysis will be scrutinised carefully to avoid any misjudgements.

Considering the pivotal importance accorded in the literature to Research and Development (R&D) activities for enabling new product introduction and technological advancement, the next Section reviews the overlap between PIC, R&D and technological capabilities.

2.3.2. PIC, R&D and technological capability overlaps

Innovation is central to R&D activities of firms (Cohen & Levinthal, 1989). Penner-Hahn and Shaver (2005: 123) aptly state that “firms undertake R&D activities in large part to create innovations that will ultimately provide new products and therefore profits.” Shoenecker and Swanson (2002: 37) similarly assert that allocation of resources to R&D “is a crucial early step in developing new products or new technologies”. Krasnikov and Jayachandran (2008: 2) define R&D capability as “processes that enable firms to invent new technology and convert existing technology to develop new products and services”. They acknowledge significant overlaps between R&D capability and PIC, in their meta-analytic review. A review of measures of the two constructs also reveals striking similarities (e.g., see Danneels, 2008; O’Cass & Ngo, 2012), that are also largely consistent with measures of dynamic capability construct as deployed by Drnevich and Kriauciunas (2011). Hence, it can be argued that R&D capability and PIC are largely overlapping constructs and calibrated using similar metrics, such as new product introductions and number of patents. In addition, technological capability often exhibits similarities in conception and operationalisation with PIC and R&D capability (e.g., see Camisón & Villar-López, 2014; Di Benedetto, DeSarbo & Song, 2008; Flor & Oltra, 2005; Huang, 2011; Lefebvre, Lefebvre & Bourgault, 1998; Persaud, 2005; Shoenecker & Swanson, 2002; Song et al., 2005; Young & Tavares, 2004).

Differences in terminology used for virtually identical constructs, appear to have emerged as a consequence of nuances, different research foci and discrete evolutionary trajectories of largely independent research streams. Consequently, when R&D and technological capabilities are operationalised identically to PIC in studies, they (i.e., the studies) will be included in the current meta-analysis. Also, when innovation capability and innovation are operationalised similar to PIC, the studies will be included in the current meta-analysis. Such decisions are also common in other meta-analyses (e.g., see Kirca et al., 2011; Krasnikov & Jayachandran, 2008).

Given that the innovation literature reveals certain discrepancies between the conception and measurement of constructs, operationalisation of PIC is outlined next in an endeavour to evaluate the construct validity of PIC. Such an assessment builds upon the theoretical triangulation presented in the previous Section and can provide insights into the construct-level relationship of interest.

2.3.3. The preponderance of effects and resource-input measures

Underscoring the challenges involved in operationalising capabilities, Krasnikov and Jayachandran (2008), in their meta-analysis exhort researchers to undertake a detailed examination of the metrics used for the measurement of capabilities. In the context of the current meta-analysis, this is critical because the correspondence between PIC conceptualisation and measurement is imperative to attain a high level of construct validity.

2.3.3.1. Overview of PIC measures

Upon examining measurement models of PIC, the primacy of reflective measures pertaining to innovation outcomes (effects) or investments (resource inputs) can be readily observed (e.g., see Camisón & Villar-López, 2014; Delgado-Verde et al., 2011; Grawe et al., 2009; O'Cass & Ngo, 2012). Reflective measures enable the assessment of the underlying latent construct by measuring quantifiable manifestations of the construct, as the construct itself cannot be directly observed (see MacKenzie et al., 2005). The practice of employing reflective measures for PIC calibration clearly stems from the

fact that PIC is a latent construct. MacCallum and Austin (2000: 202) define latent variables as “hypothetical constructs that cannot be directly measured”. Hence, the challenge concerning the direct measurement of PIC is overcome through the use of reflective measures and a few such measures of PIC are provided in the Table 2.1.

Table 2.1: Illustrative examples of PIC effects measures

<i>Author (year)</i>	<i>Measure</i>
Grawe et al. (2009: 291)	“our firm is able to come up with new product offerings”
O’Cass & Sok (2013b: 10)	“Within this firm we have activities, routines, business processes and behaviours for developing new products”
Delgado-Verde et al. (2011: 13)	“the number of new products with respect to my product portfolio”

The pertinence and usefulness of output-oriented measures for quantifying various innovation constructs (including PIC) is widely acknowledged in the innovation literature (see Coombs, 1996; Guan, Yam, Tang & Lau, 2009; OECD’s OSLO Manual, 1992). Assertion made by Siguaw, Simpson and Enz (2006) that dynamic capabilities concerning innovation directly generate innovation outcomes, supports the use of innovation outcome-oriented measures (hence referred to as—effects measures) for capturing PIC.

Effects measures are required to be rated by respondents and are generally comparative (i.e., rated with regards to competing firms), and have acquired widespread acceptance in the scholarly community (Danneels, 2012; Zahra & Covin, 1993). Comparative qualifier statements such as those presented in the Table 2.2 are characteristically used in research for assessing PIC levels of sampled firms. The fact that comparative effects measures are generally used for operationalising PIC, informs the PIC–firm performance meta-analysis.

Table 2.2: Examples of comparative qualifiers for PIC measures

<i>Author (year)</i>	<i>Qualifiers</i>
Grawe et al. (2009: 291)	“compared to our competitors”
Hooley et al. (2005: 26)	“strong competitors’ advantage/ our strong advantage”
Morgan et al. (2009: 912), O’Cass & Ngo (2012: 129)	“much worse/ much better than competitors”

Furthermore, absolute effects measures such as, “compared to the competition, our firm is able to come up with new product offerings” (Grawe et al., 2009: 291), and relative effects measures such as, “the ratio of new products to the entire product portfolio” (Delgado-Verde et al., 2011: 13), are frequently used. Absolute measures are factual numbers or ratings by informants (versus rival firms), on scale indicators such as the number of new product introductions by a firm. Relative measures operationalise the construct through a ratio of a suitable indicator such as the number of new product introductions to a corresponding metric such as the total number of products offered by the firm. A combination of both absolute and relative measures is often used in innovation research owing to their ability to capture different aspects of the constructs under investigation (e.g., see Delgado-Verde et al., 2011).

Other measures of PIC, sometimes employed in conjunction with effects measures include indicators that attempt to measure willingness or ability of a firm to introduce new/improved products (e.g., Camisón & Villar-López, 2014; Jiménez-Jiménez & Sanz-Valle, 2011), and the speed of introducing new products/time-to-market (e.g., Akgün, Keskin & Byrne, 2009; Aragon-Correa et al., 2007; Calantone, Garcia & Dröge, 2003; Camisón & Villar-López, 2014; Garcia & Calantone, 2002; Grawe et al., 2009; Lawson, Samson & Roden, 2012; Panayides, 2006). Such measures can be contended to correspond with the dynamic capability conceptualisation, thereby supporting their use in PIC operationalisation. This is argued because time-to-market/speed of introducing new products are manifestations of the ability with which the firm

can respond and adapt to environmental shifts, which is a central characteristic of dynamic capabilities (see Eisenhardt & Martin, 2000; Teece et al., 1997). Notwithstanding the apparent suitability of PIC measures discussed in this Section, concerns about the operationalisation of innovation and dynamic capability constructs have been raised in the literature (see Camisón & Villar-López, 2014; Danneels & Kleinschmidt, 2001; Garcia & Calantone, 2002; Montoya-Weiss & Calantone, 1994; Wang et al., 2015), and discussed next.

2.3.3.2. Gaps in the validity of innovation and dynamic capability constructs

The scant attention paid to the validity of innovation constructs and the inconsistencies in their operationalisation is more concerning in the case of multidimensional constructs than with uni-dimensional constructs. For example, in the context of product innovativeness, Danneels and Kleinschmidt (2001) maintain that its measurement has often been approached unidimensionally, although the construct is multidimensional. Although some researchers have attempted to explicitly recognise and capture the multidimensionality of certain innovation constructs (e.g., see Agarwal & Selen, 2011), such attempts are sporadic. Peter (1981) argues that scale indicators seldom encompass all aspects of a multidimensional construct. Such observations point towards a frequent and distinct lack of congruency between the conceptions of multidimensional construct and their measures. Some researchers attribute this problem to intensive efforts to enhance reliability that tend to crowd out the endeavours targeted towards enhancement of construct validity (see Drolet & Morrison, 2001).

The limited focus on construct validity in the innovation literature means that the related body of empirical research may be called into question (Calantone, Harmancioglu & Dröge, 2010). Similar concerns about validity have been raised in the measurement of dynamic capabilities as well. For example, in the context of dynamic capability construct, Wang et al. (2015: 2) state that, “recent debate also surrounds its operationalization”. Hence, Weerawardena and Mavondo (2011) strongly encourage explicit and comprehensive

conceptualisation of dynamic capabilities and substantive development of their measures for the advancement of empirical research.

The contentions presented above are of particular relevance to PIC as its conception as a dynamic capability and innovation construct is multidimensional, and it is imperative to operationalise PIC as such. It is important that all dimensions of the construct are appropriately calibrated to achieve high construct validity of PIC. Hence, an examination of PIC validity is undertaken next and its measures are subjected to scrutiny from the standpoint of overlaps between DC, Ambidexterity and Process Management Theories, as identified through triangulation. Measures commonly used for operationalisation of PIC (as outlined in Tables 2.1 and 2.2) are subjected to examination so as to identify any validity problems with PIC.

2.3.4. The challenge of capturing multidimensionality

This Section outlines some prescriptions for the development of measurement models for latent constructs (such as PIC) as recommended by MacKenzie et al. (2005), and Nunnally and Bernstein (1994). The hierarchical guidelines for formulation of measurement models as prescribed by MacKenzie et al. (2005: 725) include:

- 1. Clearly define the construct domain*
- 2. Evaluate the conceptual dimensionality of the construct*
- 3. Generate a set of measures to fully represent the constructs domain*
- 4. Carefully consider the relationship between the construct and its measures.*

These guidelines appear to be the most pertinent for examining PIC operationalisation in order to assess the degree of congruency between its multidimensional conception and measurement models. The guidelines facilitate elimination of potential misspecifications in construct operationalisation, thereby enabling attainment of high construct validity (MacKenzie et al., 2005).

The use of resource-input measures, such as R&D expenditure and R&D intensity (e.g., see Hitt, Hoskisson & Kim, 1997), and number of employees to operationalise innovation and R&D capabilities, have been called into

question by many researchers (e.g., Danneels, 2012; Rosenbusch et al., 2011). In the context of second-order R&D competence (a dynamic capability construct), Danneels (2012: 49) states that, “R&D competence is related to R&D spending but only slightly so”. Thus, it can be argued that input metrics (when used without effects measures) are inadequate for capturing the multidimensionality of dynamic capabilities.

Underscoring the challenge of measuring multidimensional innovation constructs, Kaplinski and Paulino (2005) contend that for quantifying innovation processes, the exclusive use of resource-input or effects measures is insufficient. They assert that “we need to apply a range of complementary innovation indicators, in each case interpreting the results with care” (Kaplinski & Paulino, 2005: 334). Contentions fundamentally similar to those made by Danneels (2012) and Kaplinski and Paulino (2005), have been made by several researchers investigating diverse capability constructs and relationships. Numerous studies have implicitly highlighted the potential pitfalls in the deployment of resource-input metrics in operationalising capabilities (e.g., Clegg, Axtell, Damodaran, Farbey, Hull, Lloyd-Jones, Nicholls, Sell & Tomlinson, 1997; Powell & Dent-Micallef, 1997; Trott & Hoecht, 2004). These researchers report that Information Technology (IT) investments and firm performance have a modest correlation, and this lack of a robust empirical relationship has often been referred to as the productivity paradox (e.g., see Dibrell, Davis & Craig, 2008; Santos & Sussman, 2000; Stratopoulos & Dehning, 2000; Trott & Hoecht, 2004). In the context of leveraging IT investments for developing innovations, Santos and Sussman (2000: 430) state that, “IT investments, by their very nature, must be accompanied by careful redesign and/or restructuring of the organization to obtain many of the anticipated benefits of the investment”. In a similar line of reasoning, other researchers argue that superior product innovations are not guaranteed through investment of greater resources in innovation-related activities such as R&D (e.g., Rosenbusch et al., 2011; Wolff, 2007).

Therefore, a firm may devote considerable resources to innovation activities but obtain little desired results (such as introduction of new products in the market) without having cultivated capabilities that are imperative for

successfully leveraging such resources (Rosenbusch et al., 2011). By contrast, a firm with highly developed capabilities such as PIC can reconfigure and leverage limited resources into innovative revenue-generating products that confer performance benefits (Rosenbusch et al., 2011).

Conversely, it can be contended that two firms possessing comparable PIC levels are likely to differ in desired innovation outputs such as the introduction of new products, in direct proportion (i.e., assuming a linear relationship) to the scale of their resource allocations towards product innovation. For example, a firm with twice the resource allocation for product innovation activities compared to a competing firm would likely attain twice the innovation outputs, provided they possess comparable levels of PIC, *ceteris paribus* (with the contextual variables remaining constant). It can therefore be argued that in such a case, a study exclusively employing effects measures would report a much superior PIC for the former compared to the latter firm. Such a deduction would be fallacious as superior product innovation outputs for the former firm reflects superiority in resource allocations and not in PIC.

From a somewhat different perspective, it can be asserted that two firms with comparable levels of resource inputs can be deemed to possess PIC levels that are directly reflected in the effects measures of a study. This contention is predicated on the reasoning that if effects measures for one firm are found to be twice as high as the second firm, PIC of the first firm is twice the level of second, provided that resource inputs are comparable. Therefore, effects measures can be contended to directly reflect PIC levels only when deployed in conjunction with resource inputs, in such a way so as to reflect the productivity dimension. In a similar line of reasoning, Rosenbusch et al. (2011: 445), in their meta-analysis on the relationship between Innovation and SME performance, state that:

Other firms might have capabilities to create innovative offerings, production processes or valuable patents without devoting many resources to the innovation task. In so doing, the latter firms are more capable of leveraging their resources which augments firm performance. Based on these arguments associated with the productivity of the innovation process in turning innovation inputs into innovation outputs in SMEs, we expect that SME performance is

influenced more strongly by the amount of innovation outcomes than by the amount of innovation inputs.

Based on these *a priori* contentions, it is affirmed that the exclusive use of effects measures (without corresponding resource-input measures) confounds PIC calibration with the level of resource inputs, such as financial investments, skilled manpower and existing knowledge. It is via simultaneous consideration of the two types of measures that the degree of efficiency with which resource inputs are utilised (to generate product innovation outcomes), can be captured. The two measures are therefore required to be combined in a manner that reflects relative efficiency of resource utilisation by the firms investigated in primary studies. It is concluded that the oversight of efficiency dimension in PIC operationalisation causes a critical problem with the construct validity of PIC. The current research attempts to overcome this problem with a new methodology proposed in the current study.

As previously noted, the role of dynamic capabilities under the conditions of environmental dynamism has been a focal point of research attention in DC Theory (e.g., Day, 2011; Drnevich & Kriauciunas, 2011; Eisenhardt & Martin, 2000; Schilke, 2014). It has spurred substantial interest in the relationship of dynamic capabilities with firm performance (Arend & Bromiley, 2009; Barreto, 2010; Vogel & Güttel, 2013). Therefore, the nature of PIC–firm performance association is discussed next, alongside the potential moderation impact of environmental dynamism on the relationship of interest.

2.4. UNDERSTANDING THE PIC–FIRM PERFORMANCE LINK

While the proponents of DC Theory maintain a positive relationship of PIC with firm performance (e.g., Eisenhardt & Martin, 2000; Teece et al., 1997), the literature often presents conflicting findings regarding the relationship. Although a majority of studies demonstrate a positive influence of product innovation on firm performance (e.g., Calantone et al., 2002; Cui, Griffith & Cavusgil, 2005; Dai & Liu, 2009; Panayides, 2006; Ettlie & Pavlou, 2006;

O'Cass & Sok, 2013b), a few also report a negative association (e.g., Katila & Ahuja, 2002; Penner-Hahn & Shaver, 2005; Thornhill, 2006). Additionally, the study conducted by Drnevich and Kriauciunas (2011) reports a negative correlation between dynamic capabilities and relative firm-level performance (frequently employed as an empirical equivalent of competitive advantage). On the other hand, Schilke (2014) reports a positive correlation between dynamic capabilities and relative firm performance, supporting the theoretical tenets of DC Theory. Such divergent results indicate that a systematic aggregation of findings is required for gaining a better understanding of the magnitude and direction of the association between PIC and firm performance. The divergence also warrants an assessment of potential moderators that may influence the focal relationship.

A moderator is a variable whose value determines the magnitude or direction of the relationship between the independent and dependent variables (Aguinis & Pierce, 1998). In other words, a relationship between two variables would vary in direction and/or strength depending upon the level of a moderator. Geyskens, Krishnan, Steenkamp and Cunha (2009) strongly recommend identification of moderator variables via examination of the theoretical arguments contained in the literature. Hence, given the crucial significance accorded to market dynamism in innovation literature and DC Theory, and recent attempts undertaken to calibrate its moderation effects, market dynamism is discussed next (e.g., see Drnevich & Kriauciunas, 2011; Schilke, 2014; Wang et al., 2015; Wilhelm et al., 2015).

2.4.1. Market Dynamism: A Potential Moderator

Investigation of the drivers that enable organisational adaptation to match environmental change is a dominant theme in research (e.g., see Benner, 2009; Helfat et al., 2007; Levinthal & March, 1993; Lichtenthaler, 2009; March, 1991; Nohria & Gulati, 1996; Sirmon, Hitt, Arregle & Campbell, 2010; Voss & Voss, 2000; Zollo & Winter, 2002). Proponents of DC Theory contend that the disparity amongst the performance of firms is (partly) a consequence of varying degrees of compatibility between market dynamism and endowments of dynamic capabilities (e.g., Eisenhardt & Martin, 2000; Makadok, 2001;

Teece et al., 1997). These authors accord significance to the contribution of dynamic capabilities to performance under moderate to highly turbulent conditions. In a similar vein, Wang and Ahmed (2007: 34) state that, “the concept of dynamic capabilities is intrinsically linked to market dynamism”. Dynamic capabilities enable a firm to factor in ever-changing market dynamics through the effective redeployment and leveraging of resources and operational capabilities (Lengnick-Hall & Wolff, 1999; Makadok, 2001; Teece et al., 2007; Zollo & Winter, 2002). In addition to DC Theory, the impact of market dynamism has been subjected to empirical testing in the innovation literature (e.g., see Calantone et al., 2003; Hult et al., 2004; Jiménez-Jiménez & Sanz-Valle, 2011; Li & Atuahene-Gima, 2001; 2002; Miles, Covin & Heeley, 2000; Thornhill, 2006).

A review of the terms environmental, market and industry dynamism (or turbulence) reveals that these constructs have been conceptualised and operationalised in virtually identical manner in a majority of studies examining capability and innovation constructs (e.g., see Atuahene-Gima, 2005; Calantone et al., 2003; Calantone et al., 2010; Cui et al., 2005; Eisenhardt & Martin, 2000; Garg, Walters & Priem, 2003; Helfat & Winter, 2011; Jiménez-Jiménez & Sanz-Valle, 2011; Li & Atuahene-Gima, 2002; Li & Liu, 2014; Schilke, 2014; Sirén et al., 2012; Thornhill, 2006; Vincent, Bharadwaj & Challagalla, 2004). Additionally, Davis, Eisenhardt and Bingham (2009) and Kirca et al. (2005) interchangeably use the terms market dynamism and environmental dynamism, and market turbulence and environmental turbulence, respectively. They highlight complexity, rate of change and unpredictability as the central aspects of the construct.

Damanpour (1996) and Tidd (1995; 1997; 2001) underscore the focus in innovation literature on uncertainty and complexity. Tidd (2001: 175) states that, “two contingencies exert significant influence on the organisation and management of innovation: uncertainty and complexity”. Hence, it is contended that the essence of the terms (i.e., environmental, market and industry dynamism) in strategic management and innovation literatures are largely the same. Considering the very little (if any) identifiable difference

amongst the terms, market dynamism is the term used in the current study to represent the construct, as it corresponds to much of the DC Theory literature (e.g., Eisenhardt & Martin, 2000; Vogel & Güttel, 2013).

It should be noted that several studies centred on market orientation (e.g., Han, Kim & Srivastava, 1998; Jaworski & Kohli, 1993), with few also encompassing dynamic capability and innovation (e.g., Menguc & Auh, 2006) conceptualise market turbulence as a component of environmental turbulence. Such a treatment of the two terms does not contradict the review and contentions presented in this Section, as the terms are used somewhat differently in the market orientation and innovation literatures. The use of the construct (i.e., market dynamism) in the current study complies with the conceptualisation as generally subscribed to in the innovation and DC Theory literatures (see Davis et al., 2009; Eisenhardt & Martin, 2000; Tidd, 1995; 1997; 2001).

A priori, dynamic capabilities (e.g., PIC) are expected to contribute more towards firm performance under the conditions characterised by high market dynamism, rather than low dynamism (Eisenhardt & Martin, 2000; Song et al., 2005). The relevance and contribution of dynamic capabilities to performance under such conditions is a core contention of DC Theory (see Schilke, 2014; Wilhelm et al., 2015). Investigating this contention, Drnevich and Kriauciunas (2011) report empirical support for a greater contribution of dynamic capabilities to relative firm performance in highly dynamic markets, than in relatively stable markets. Whereas, Schilke (2014) reports an inverse U-shaped moderation effect of market dynamism on the association between dynamic capabilities and (relative) firm performance, indicating that dynamic capabilities have stronger association with firm performance under moderate dynamism. These studies, the former suggesting a largely linear relationship and the latter a non-linear one, illustrate the divergence prevailing in the literature. Furthermore, the moderating effect of market dynamism on the association between dynamic capabilities and firm performance remains under-researched (Wilhelm et al., 2015).

Also, in the innovation literature, studies often report divergent results on the moderation effect of market dynamism on the innovation–firm performance relationship. For example, Li and Atuahene-Gima (2001) report a positive effect of market dynamism on the relationship between product innovation and performance of new technology ventures in China. However, Hult et al. (2004) and Thornhill (2006) report a non-significant moderation impact of market dynamism on the innovation–firm performance relationship. By contrast, Jiménez-Jiménez and Sanz-Valle (2011) report a negative moderation effect of market dynamism on the relationship. The conflicting findings indicate that a meta-analytic investigation concerning the moderation effect of market dynamism can shed light on the boundary conditions of the PIC–firm performance relationship. Thus, due to mixed findings and relative scarcity of empirical evidence on moderation by market dynamism in DC Theory and innovation literatures, its moderation effects on the focal relationship will be inferred in this study, via a direct examination of technological turbulence.

2.4.2. Technological turbulence as a driver of market dynamism

It is widely acknowledged that market dynamism is accelerating (e.g., see Day, 2011; Eisenhardt & Martin, 2000; Makadok, 2001). Technological uncertainty is also increasing rapidly (Song & Montoya-Weiss, 2001), and the advances in technology have contributed chiefly to enhancing market dynamism (Day, 2011). The acceleration in market dynamism is demonstrated by an examination of anecdotal evidence pertaining to technological turbulence in global markets (Day, 2011). For instance, the proliferation in the number of mobile telephony service plans, applications for handheld devices, and value added services (such as internet browsing, multi-media messaging) demonstrate a higher level of market dynamism that is chiefly spurred by technological advancements.

The literature widely recognises the impact of technological turbulence on the relationships of various constructs with firm performance (e.g., see Gatignon

& Xuereb, 1997; Grinstein, 2008b; Han et al., 1998; Jiménez-Jiménez & Sanz-Valle, 2011; Kirca et al., 2005; Song et al., 2005). Several researchers claim that under the conditions of high technological turbulence, innovation outcomes are driven more by R&D initiatives rather than customer orientation (e.g., Gatignon & Xuereb, 1997; Grewal & Tansuhaj, 2001; Kohli & Jaworski, 1990). This contention is widely supported in the literature, suggesting that during times of high technological turbulence, customer feedback may only facilitate formulation of reactive (as opposed to proactive) strategies (e.g., see Atuahene-Gima, 2005; Atuahene-Gima, Slater & Olson, 2005; Calantone et al., 2010).

Calantone et al. (2010: 1076), in their meta-analytic review conclude that “rapid technological advancements, but not necessarily uncertainties in customer expectations and competitive intensity, seem to encourage firms to innovate”. They report statistically significant results for the association between technological turbulence and innovation but non-significant results for market turbulence and innovation, with market turbulence in their study capturing shifts in customer preferences and competitive landscape. This finding supports the view and anecdotal evidence that technological turbulence is the primary driver of market dynamism.

Additionally, consistent with Audretsch and Acs (1991), Thornhill (2006) operationalises market dynamism by employing R&D intensity as a measure, in addition to the percentage of knowledge workers (e.g., R&D employees). Such an operationalisation of market dynamism is consistent with the assertion that R&D activities, and consequently technological turbulence, is a major determinant of market dynamism in the current business landscape.

Thus, the PIC–firm performance link is expected to vary in magnitude and/or direction, depending on the extent of prevailing technological turbulence. Consequently, an empirical investigation of potential moderation effect of technological turbulence on PIC–firm performance association is called for, as also recommended by Krasnikov and Jayachandran (2008). Hence, a direct assessment of the moderation effect of technological turbulence on the relationship of interest is undertaken in the current study. A direct assessment

of technological turbulence as a moderator is expected to shed light on the moderation effect of the broader market dynamism construct, as technological turbulence is argued to be the primary driver of market dynamism. For enabling a meta-analysis of the relationship of interest, an outline of measures deployed for operationalising firm performance is presented next.

2.5. MEASURES OF FIRM PERFORMANCE

An examination of the empirical literature on firm performance reveals that the most commonly employed measures of performance are objective measures that include financial and market-oriented metrics, and subjective measures that are constituted by scale ratings of informants. Commonly employed objective measures (financial and market-oriented) of firm performance are enumerated in Table 2.3.

Table 2.3: Objective firm performance measures used frequently in studies

<i>Financial Performance Measures</i>	<i>Market-Oriented Measures</i>
ROA (Return on Assets)	Market-share
ROS (Return on Sales)	Market-share growth
Overall profitability	Sales revenue
Tobin's Q	Sales growth
ROI (Return on Investments)	Customer-oriented measures

The literature unequivocally suggests that market-oriented and financial measures are mutually interdependent and reflective; consequently, they are frequently combined to collectively reflect overall firm performance (Weerawardena, 2003). Similarly, Merrilees et al. (2011) argue that although the link between market and financial performance may not be perfectly proportionate, it is likely to be very strong. A meta-analysis conducted by Combs, Crook and Shook (2005) on firm performance metrics demonstrates a strong correlation between financial and market-oriented performance measures. This meta-analytic finding underpins the contention by Weerawardena (2003) and Merrilees et al. (2011) that the two sets of firm performance measures exhibit a high level of equivalence and interchangeability. This suggests that these measures can be combined and used in the current meta-analysis, as also adopted in other meta-analyses (e.g., see Krasnikov & Jayachandran, 2008; Rosenbusch et al., 2011).

Researchers also argue for the existence of a strong correlation between objective (financial and market-oriented) and subjective (self-reported) measures of firm performance (e.g., see Dess & Robinson, 1984). A few meta-analytic reviews focussing on firm performance synthesise effect sizes based on both (i.e., objective and subjective) performance measures (e.g., see Rosenbusch et al., 2011). Consequently, in the current study, effect sizes based on objective measures are synthesised alongside self-reported measures. As self-reported metrics of firm performance are commonly used in empirical research (see Combs et al., 2005), their inclusion in the meta-analysis also serves to enhance the statistical power of the study by allowing for the incorporation of a greater number of studies.

Given that several meta-analyses have focused on firm performance, a few meta-analyses that have investigated the effects of various innovation constructs on firm performance are reviewed next. The following review explicates these meta-analyses in terms of their scope and key findings.

2.6. REVIEW OF META-ANALYSES INVESTIGATING INNOVATION CONSTRUCTS AND FIRM PERFORMANCE

Several meta-analytic reviews have been undertaken to synthesise findings concerning the association of various capability/innovation constructs with firm performance (e.g., Bowen, Rostami & Steel, 2010; Büschgens, Bausch & Balkin, 2013; Krasnikov & Jayachandran, 2008; Rosenbusch et al., 2011; Sivasubramaniam, Liebowitz & Lackman; 2012). Evidently, the publication of a seminal meta-analysis on innovation by Damanpour (1991) generated substantial scholarly interest in the research community and yielded a sizeable meta-analytic literature in the innovation domain.

Many meta-analyses deploy innovation constructs as the dependent variable (DV) (e.g., Büschgens et al., 2013; Evanschitzky, Eisend, Calantone & Jiang, 2012; Henard & Szymanski, 2001; Sivasubramaniam et al., 2012). Others have investigated innovation constructs such as innovativeness and R&D capability, as the independent variable (IV) (e.g., Bowen et al., 2010; Rosenbusch et al., 2011; Rubera & Kirca, 2012). Additionally, some meta-analyses model innovation as both IV and DV, thus, investigating innovation as both a potential antecedent and consequence of other variables (e.g., Calantone et al., 2010). Due to PIC and firm performance being the IV and DV (in this study), respectively, meta-analyses investigating the relationships between innovation/capability constructs and firm performance are discussed here to assess their contribution to the literature and highlight any gaps.

Meta-analysis by Krasnikov and Jayachandran (2008) evaluated the strength of relationships between three operational capabilities (namely, marketing, R&D and operations capability) with firm performance. Their study is the only attempt to statistically synthesise empirical findings on capability–firm performance relationships. Summary effect sizes reported in their study were 0.352, 0.275 and 0.205 for marketing, R&D and operations capabilities respectively, and represent the magnitude of their relationship with firm performance metrics. The reported summary effect sizes indicate the

strongest link with performance for marketing capability, followed by R&D and operations capabilities. Importantly, in addition to the three capabilities, the study encompasses PIC and codes it as identical to R&D capability in specific cases. This is a noteworthy aspect of Krasnikov and Jayachandran (2008) study as the inclusion of PIC in their study causes some overlap with the present meta-analysis.

In Krasnikov and Jayachandran's (2008) study, the synthesised correlations were often based on resource-input measures for R&D capability and PIC, such as R&D expenditure and intensity. Such measures are however, inadequate for capturing dynamic capability constructs (as explicated earlier in this Chapter), and no distinction between resource-input and effects measures were made in summary effect size computation. Therefore, it is argued that R&D capability and PIC, in Krasnikov and Jayachandran's (2008) study are not modelled as dynamic capability constructs and this offers research opportunities for undertaking further data syntheses. Additionally, PIC is incorporated only perfunctorily in their study, thereby lacking a rigorous examination of its association with firm performance, as also acknowledged by the authors. They encourage further meta-analytic examination of PIC and performance, and highlight the challenges involved in operationalising higher-order (dynamic) capabilities that are multidimensional.

Two further meta-analyses investigating innovation and its relationship with firm performance, have been conducted, namely, Rosenbusch et al. (2011) and Bowen et al. (2010), with both examining the association between innovation and firm performance. Besides the focal relationships, the two studies also investigated the types of innovation metrics as moderators of the relationships of interest. A further meta-analysis by Rubera and Kirca (2012) investigated the relationship of innovativeness with different measures of firm performance. Their study employs the chain-of-effects model (see Rust, Ambler, Carpenter, Kumar & Srivastava, 2004), linking innovativeness to firm value, in order to ascertain the extent to which the constructs are inter-correlated. The mediating role of market and financial measures in the innovativeness–firm value relationship was examined in the Rubera and Kirca

(2012) study, alongside moderation effects of variables such as firm size and advertising intensity. Table 2.4 summarises the salient characteristics and findings of these three meta-analyses.

Table 2.4: The scope and findings of meta-analyses investigating the relationships between innovation constructs and firm performance

<i>Meta-analyses (Author, Year)</i>	<i>Core Constructs</i>	<i>Moderator Variables</i>	<i>Meta-analytic Findings</i>
1. Bowen et al. (2010)	IV-Innovation, DV-firm performance	Innovation stage, type, specificity and scope; Performance type; and firm size	Positive relationship; also influenced by moderators
2. Rosenbusch et al. (2011)	IV-Innovation, DV-SME performance	Innovation type, firm age and individualism	Positive relationship; also influenced by moderators
3. Rubera and Kirca (2012)	IV-Firm innovativeness DV-firm performance	Firm size, advertising and technology intensity, national culture etc.	Positive relationship; also influenced by moderators

The Rosenbusch et al. (2011) study modelled innovation (IV) as a process and examined the SME performance and innovation relationship, with innovation operationalised through both effects and resource-input measures. The process-based conception of innovation pertains to the ability of firms to efficiently convert resource inputs (e.g., financial allocation for and the number of employees in R&D) into performance-enhancing innovative outputs (e.g., new product introductions in the market). Two separate summary effect sizes were therefore computed for each type of metric (i.e., resource inputs and effects) by Rosenbusch et al. (2011). The comparison of the two summary effect sizes revealed a significant difference in the association of the two

innovation measure types with firm (i.e., SME) performance. The difference in the magnitude of summary effect sizes was due to the choice concerning the use of either resource inputs or effects measures, on which the effect sizes were based on. The authors attribute these differences to be a consequence of the disparate innovation capability endowments of firms and, therefore, varying efficiencies of resource utilisation. They maintain that innovation capability enables firms to effectively transform resource inputs (such as financial allocation for R&D and knowledge), into performance-enhancing innovative outputs, such as revenue-generating products. Implicitly, this suggests that the relative innovation capability endowments of firms are reflected through the simultaneous consideration of effects measures and corresponding resource inputs, so that the efficiency dimension is appropriately accounted for.

The meta-analysis by Rosenbusch et al. (2011), however, did not report a singular summary effect size that factored in both resource inputs and innovation effects simultaneously, and this gap is also addressed in the present research. Furthermore, although the theoretical underpinnings of the meta-analysis by Rosenbusch et al. (2011) were robust, the study suffered from a serious methodological flaw of not correcting synthesised effect sizes for measurement errors. This is argued because corrections for reliabilities were not reported in their study, and Geyskens et al. (2009) contend that in absence of such information, it is reasonable to conclude that corrections have not been undertaken. It is critical to perform such corrections so as to enhance the accuracy of the summary effect size, and meta-analyses generally undertake such corrections (e.g., see Bowen et al., 2010; Grinstein, 2008a; 2008b; Kirca et al., 2005; Kirca, Hult, Roth, Cavusgil, Perry, Akdeniz, Deligonul, Mena, Politte, Hoppner, Miller & White, 2011; Krasnikov & Jayachandran, 2008).

On the basis of the content analysis presented here, it is concluded that the statistical syntheses thus far conducted of innovation constructs do not model innovation capability from DC Theory lens and gaps in the literature persist. The resource productivity dimension of PIC remains unspecified in meta-

analyses, in much the same way (and also consequent to), as it has remained unspecified in primary studies. Thus, further research is required to bridge this gap prevailing in the innovation and DC Theory literatures.

2.7. CHAPTER SUMMARY

The Chapter presented a theoretical triangulation of three prominent theories (i.e., DC, Process Management and Ambidexterity) and identified certain overlaps between them. The salient outcome of triangulation concerned the oversight of efficiency dimension of PIC, thereby bringing the construct validity of PIC into focus.

Through a review of DC Theory and innovation literatures, the Chapter highlighted gaps that exist in the literature, and revealed deviations from what is proposed theoretically but actually encountered in the empirical literature. It was argued that due to the differences in the findings concerning the direction and magnitude of the PIC–firm performance link, a systematic synthesis of findings is called for. Thus, a meta-analysis on the relationship of interest in order to assess its magnitude, and to shed light on potential moderators, is undertaken in the present study.

The following Chapter presents a novel framework for conducting the PIC–firm performance meta-analysis. The meta-analysis will examine the relationship from the standpoint of PIC construct validity, and proposes a framework that aims to overcome the validity problem of PIC, as identified in this Chapter. The proposed framework is predicated on the literature review and builds on the contentions presented in the current Chapter. The next Chapter will also present hypotheses concerning the relationship of interest and its potential moderators.

CHAPTER THREE

THEORY DEVELOPMENT

3.1. INTRODUCTION

This Chapter builds on the previous one which presented a review of DC Theory and innovation literatures, theoretical triangulation and content analysis of meta-analytic reviews. The Chapter presented gaps in the literature, in particular, those concerning construct validity of innovation and dynamic capability constructs, and the contradictory empirical findings on the PIC–firm performance relationship. The theoretical triangulation and relevant *a priori* arguments, collectively served as a lens to assess the congruence between the conceptualisation and measurement of PIC. It was established that a meta-analysis is required that systematically aggregates the often contradictory findings on the relationship of interest.

In the current Chapter, the theoretical overlaps between the three theories are employed for establishing that the dimension of PIC concerning efficiency of resource utilisation is required to be incorporated in PIC operationalisation. Thus, it is argued that through the incorporation of the productivity dimension, the construct validity problem of PIC can be largely overcome. The Chapter presents the underpinnings of a unique framework for conducting a meta-analysis on the PIC–firm performance relationship.

The proposed framework aims to overcome the identified PIC validity problem by factoring in the unspecified resource productivity dimension *post hoc*. Consequently, a higher level of PIC construct validity can be achieved by accounting for the relative resource inputs (by sampled firms), via employment of a set of computational procedures (i.e., weighting scheme). The enhancement of construct validity aids in gaining insights into the true association of interest, and its potential moderators (Geyskens et al., 2009; Hunter & Schmidt, 2004).

Thereafter, the Chapter presents testable moderation hypotheses concerning the relationship of interest. Determining the presence of moderation effects allows for a deeper understanding of the boundary conditions for the relationship, which is vital for the expansion of DC Theory and innovation literatures (see Aguinis et al., 2011; Viswesvaran & Ones, 1995).

3.2. INCORPORATION OF THE PRODUCTIVITY DIMENSION TO CAPTURE PIC MULTIDIMENSIONALITY

In accordance with the contentions presented in Section-2.3 (and the PIC definition by O'Cass & Ngo, 2012), the use of effects measures for operationalising PIC is deemed appropriate in the current study, but such measures are deficient and do not enable a comprehensive calibration of PIC. The deficiency in effects measures arises on account of the productivity dimension of PIC (i.e., the efficiency with which resources are exploited) not being reflected in such metrics. Hence, the correlations that are computed from the effects measures of PIC are included in the dataset, but subsequently modified so that the relative resource-inputs can be accounted for. In other words, the modifications to correlations (based on the effects measures of PIC) via the weighting scheme aim to incorporate the efficiency dimension. The decision to include effects measures-derived correlations stems from scholarly contentions that ascribe an innovation outcome-generating and exploratory role to dynamic capabilities (e.g., PIC) as outlined in the previous Chapter (e.g., see Day, 2011; Siguaw et al., 2006).

The process-based conception of PIC further underpins the need to consider both resource inputs and effects, as they represent extremities (i.e., end-points) of the product innovation process. It is evident that PIC operationalisation from Process Management's locus of productivity is vital and is intrinsic to the process-based view of dynamic capabilities (as discussed in Section-2.2). This approach can also enable the

multidimensionality of PIC to be accounted for, causing the construct validity of PIC to be enhanced.

As already stated, due to the productivity dimension concerning the relative efficiency of resource utilisation having been overlooked in the literature, the proposed weighting scheme attempts to incorporate this facet of PIC. Enhancement of PIC construct validity is a pre-requisite for the PIC–firm performance meta-analysis, as a lack of construct validity can eventuate in erroneous empirical conclusions (see Cronbach, 1971; Peter, 1981). It is concluded that the construct validity problem of PIC essentially stems from a lack of simultaneous consideration of resource input and product innovation outcomes (i.e., effects), in a manner that factors in the efficiency dimension. The Figure 3.1 depicts this contention that is underpinned by theoretical triangulation.

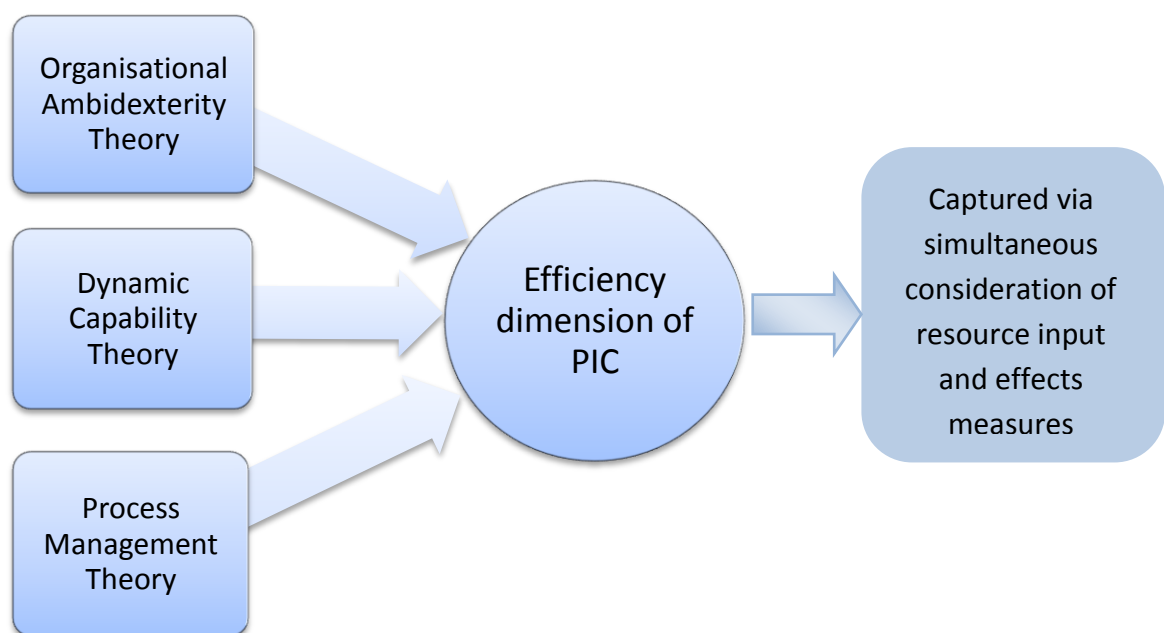


Figure 3.1: The convergence on efficiency of resource utilisation

As highlighted previously, the concurrent use of resource input and effects measures (in addition to other valid measures outlined in Section-2.3.)

constitute a more comprehensive PIC measurement approach. From the Ambidexterity standpoint, such an operationalisation accounts for both exploitative and exploratory roles of PIC, with the former (i.e., exploitative) reflecting the efficiency dimension. However, the unavailability of resource allocation data alongside the data for product innovation outcomes is a critical measurement constraint for capturing the productivity aspect of PIC.

Meta-analysts maintain that modifications in reported correlations, via computational procedures, are sometimes warranted (e.g., Lipsey & Wilson, 2001; Schmidt & Hunter, 1996). While most meta-analyses do not undertake corrections for construct validity problems (Hunter & Schmidt, 2004), the current study accounts for the validity problem in PIC. Corrections to enhance construct validity are essential as relationships represented by imperfect measures that fail to appropriately operationalise constructs should not be the ultimate aim of scientific enquiry (Geyskens et al., 2009; Schmidt & Hunter, 1996). Stated differently, rather than investigating the observed relationship as represented through imperfect measures (Aguinis & Pierce, 1998; Schmidt & Hunter, 1996), an endeavour is made to unravel the construct-level relationship of interest by undertaking adjustments in reported correlations. On the basis of the preceding arguments, it is affirmed that efforts to enhance construct validity of PIC are essential, as it bears upon the relationship of PIC with firm performance.

Schmidt and Hunter (1996: 200) provide several situation-specific examples of such modifications and state that “if a large error component is missed by the method used in a given study, then correction using the reliability estimate may be only partial correction”. Hence, for incorporating the unspecified efficiency dimension of PIC, customary meta-analytic corrections (such as for reliability errors), though necessary, are clearly not sufficient.

This study proposes that overcoming the construct validity problem of PIC arising from the omission of the productivity dimension is possible through the use of methodological procedures entailing adjustments in reported correlations. In order to obtain a summary effect size representing the

construct-level relationship and detection of its moderation effects, a meta-analytic model is presented in this Chapter. The model comprises an effect size weighting scheme, in addition to other meta-analytic procedures that are commonly employed, such as those for obtaining summary effect size and estimating moderation effects. The underpinnings and theoretical contentions of the weighting scheme are discussed in the current Chapter and the details of the computational procedures are explained in the next Chapter.

The weighting scheme features procedures that enable adjustments in reported effect sizes to account for the relative resource commitments (of sampled firms) towards product innovation. As mentioned earlier, factoring in of the relative resource inputs in conjunction with the effects measures, via the proposed scheme is contended in this study to account for the productivity dimension of PIC. The weighting scheme aims to address the construct validity problem of PIC and yield results that potentially enhance the understanding of construct-level relationship of interest, rather than the association between imperfect measures of PIC and firm performance. The scheme aids in the attainment of high construct validity for PIC, which is a necessary condition for the development of empirical literature, and for undertaking a substantive meta-analysis for the focal relationship (see Thorndike & Hagen, 1977).

Due to the uniqueness of the research problems confronted by meta-analysts, no generic prescriptions are available in the literature for undertaking such effect size adjustments. For example, Lipsey and Wilson (2001) opine that effect size adjustments beyond the conventional corrections for errors, such as measurement errors (for reliability) and range restriction, are sometimes necessary prior to meta-analytic computations. But, they do not offer any guidelines, citing situational variations and complexities involved in such adjustments. Thus, in order to execute adjustments in individual correlations representing the PIC–firm performance relationship, before conducting their synthesis, the weighting scheme is devised and presented next. As stated earlier, the proposed scheme attempts to incorporate both the resource-input

and effects measures in PIC measurement, thereby enabling capturing of the productivity dimension of PIC.

3.3. THE UNDERPINNINGS OF THE EFFECT SIZE WEIGHTING SCHEME

Making appropriate corrections for imperfect measurement is often necessary, with methodological literature unequivocally corroborating this view (Schmidt & Hunter, 1996). Similarly, Lipsey and Wilson (2001: 107) argue that “in many meta-analyses it may be appropriate to adjust individual effect sizes for bias, artefact, and error prior to any statistical analysis”. Construct validity errors are likely to be more pronounced in the case of multidimensional latent constructs (e.g., PIC); as such constructs are not directly measured, but are operationalised through overt manifestations (see Mackenzie et al., 2005; Nunnally & Bernstein, 1994). Imperfect construct validity is consequent to either random or systematic errors in the measurement of variables (Hunter & Schmidt, 1990; 2004). In the case of PIC, the latter problem (i.e., a systematic error) occurs due to the consistently unspecified productivity dimension. Hence, the weighting scheme addresses this systematic measurement error.

The proposed weighting scheme enables computation of weights that are subsequently converted to adjustment factors. These study-specific adjustment factors are assigned to corresponding correlations for modifications. The assignment of adjustment factors is argued to account for the productivity dimension of PIC. The fundamental arguments guiding the calculation and assignment of adjustment factors to the reported correlations are:

- 1) If the measurement of PIC in the (primary) incorporated studies were to account for the productivity dimension, the magnitude of its relationship with firm performance, as represented by a correlation would undergo a corresponding change.
- 2) If the correlations computed on the basis of effects measures of PIC are modified by adjustment factors to account for relative resource inputs, the

productivity dimension can be accounted for. This means that the construct validity problem of PIC can be addressed *post hoc*.

3) Through a statistical aggregation of individually adjusted correlations, the magnitude of the construct-level relationship of interest can be estimated via a summary effect size. This summary effect size is posited to be a superior estimate of the underlying (true) relationship, than a summary effect size computed on the basis of unadjusted correlations.

As a possible solution to the constraint of unavailability of resource input data from incorporated studies, the characteristics of firms that reflect resource inputs were explored to identify a proxy measure for relative resource inputs. The following discussion outlines the basis for selecting average firm size (as the firm size of sampled firms is generally reported as average and not for each sampled firm) as a proxy for relative resource inputs. The discussion commences with a brief literature background and then establishes the suitability of employing firm size as the proxy for innovation resource inputs, in the proposed weighting scheme.

3.3.1. Average firm size as a proxy for resource commitments

Innovation and firm performance effects of organisational size have been a focal point of research attention for decades (e.g., see Acs & Audretsch, 1987; Aiken & Hage, 1971; Audretsch & Acs, 1991; Damanpour, 1991; 1992; Hage, 1980; Jervis, 1975; Rosenbusch et al., 2011; Rubera & Kirca, 2012; Schumpeter, 1934; 1942). Several meta-analyses have also investigated the relationship between organisational size and innovation (e.g., Camisón-Zornoza, Lapiedra-Alcamí, Segarra-Ciprés & Boronat-Navarro, 2004; Damanpour, 1992). In addition, a few meta-analyses centred on innovation-focussed constructs have investigated the moderation effects of firm size on different relationships of interest (e.g., Bowen et al., 2010; Grinstein, 2008b; Rubera & Kirca, 2012).

Researchers subscribe to the viewpoint that large firms are endowed with greater resources (e.g., see Damanpour, 1992; Ettlie & Rubenstein, 1987;

Jiménez & Sanz-Valle, 2011; Laforet, 2008; Rogers, 2004; Schilke, 2014). Rubera and Kirca (2012: 133) state that “large firms can deploy more resources”, and Scherer (1982: 234) asserts in a similar line of reasoning that, “size is conducive to vigorous conduct of R&D”. Ettlie and Rubenstein (1987) argue that large firms possess greater slack resources. Slack resources are surplus resources exceeding the minimal operational requirements of a firm in generating targeted performance levels (Nohria & Gulati, 1996). Slack resources have been demonstrated to facilitate product innovation in firms possessing such resources (e.g., see Liu, Ding, Guo & Luo, 2014; Voss, Sirdeshmukh & Voss, 2008), and such resources are expected to increase with increasing firm size.

Hence, the following arguments are made in support of employing the average size of sampled firms, reported in incorporated studies, as the proxy for relative resource inputs in the weighting scheme:

- 1) Firm size reflects the magnitude of resources committed to innovation activities, and
- 2) Firm size can be effectively deployed as a proxy for resource inputs, as it is frequently reported in empirical studies.

Therefore, the average size of sampled firms is used in the weighting scheme as a proxy for product innovation resources to overcome the problem of resource-input data unavailability. To use firm size as a proxy, a fundamental decision concerning the appropriateness of employing either raw firm size data (i.e., absolute values) or log-transformed data needs to be made. Firm size data is often transformed into logarithmic values for use as a variable (see Atuahene-Gima, 2005; Danneels, 2012; Drnevich & Kriauciunas, 2011), or sometimes as absolute values (e.g., Deeds, Decarolis & Coombs, 1998; Yalcinkaya, Calantone & Griffith, 2007). One of the principal rationales for using log-transformed values of raw data is to systematically reduce variance in the absolute firm size values (Camisón-Zornoza et al., 2004; Damanpour, 1992; Kimberly & Evanisko, 1981). The other rationale favouring log-

transformations is contingent upon the nature of hypothesised relationship between the variables (Kimberly & Evanisko, 1981). The latter rationale and the suitability of using log-transformed values of average firm size in the weighting scheme are discussed next.

3.3.2. The curvilinearity of association between firm size and resource commitments

It is vital to determine whether a bivariate relationship is curvilinear or linear (i.e., directly proportional) as it dictates the choice between raw or log-transformed values in statistical calculations (Blau & Schoenherr, 1971; Kimberly, 1976; Kimberly & Evanisko, 1981). Notwithstanding, the importance of establishing the theoretical contention of curvilinearity in hypothesised relationships in order to justify the use of log-transformations, it is seldom appreciated by researchers (Kimberly, 1976; Kimberly & Evanisko, 1981).

Curvilinearity means that in a bivariate relationship, one variable increases with the other, at a decreasing rate (Child, 1973b). In other words, when one variable undergoes a change, the other variable also changes, but to a lesser extent than the first. In the context of the association of firm size with other organisational variables, Kimberly and Evanisko (1981: 701) state that “curvilinearity exists when the correlation between a variable and the log of size exceeds the correlation between the raw size measure and that variable.” Several organisational variables have been demonstrated to exhibit curvilinear relationships with firm size (e.g., see Blau & Schoenherr, 1971; Child, 1973b; Holdaway & Blowers, 1971; Indik, 1964; Kimberly & Evanisko, 1981).

In the present study, the organisational variable in question is resource allocations towards product innovation, and its curvilinear relationship with firm size is hypothesised here. The contention of curvilinearity between firm size and resource commitments is predicated on notions of the critical mass perspective, the law of diminishing returns and also empirical imperatives.

From a critical mass perspective, it is argued that as a firm expands its scale of operations, additional resource commitments to product innovation activities that are proportionate to increasing firm size, may become less desirable (see Kimberly & Evanisko, 1981). This is chiefly because, once resource commitments to product innovation have attained a critical mass, firms are less likely to be motivated to allocate scarce resources towards product innovation, in direct proportion to their increasing size. Thus, the firms would increasingly prefer to allocate the remaining resources to other critical success factors. Implicit in this argument is the strategic aim of organisations to optimally allocate finite resources towards competing ends (see Porter, 1985).

Complementary to the above viewpoint (i.e., critical mass perspective) and predicated on the law of diminishing returns (see Douglas, 1948; Shephard & Färe, 1974; Spillman & Lang, 1924), is the expectation that firms are highly alert of performance gains via the investments made towards product innovation activities. This is because, the returns are likely to grow at a diminishing rate with escalating firm size and resource availability, causing the firms to slow down further resource investments in product innovation activities. This viewpoint is consistent with the innovation literature as researchers contend that R&D efficiency has a propensity to diminish with increases in firm size and resource allocations (e.g., Camisón-Zornoza et al., 2004; Scherer & Ross, 1990). These arguments, based on the critical mass perspective and law of diminishing returns, suggest a curvilinear relationship between firm size and resource allocations towards product innovation. The curvilinearity in the association between resource allocations and firm size is a pivotal contention for the employment of log-transformed firm size as the proxy for resource allocations.

Furthermore, log-transformations are warranted for variance reduction in datasets in which the values vary considerably (Child, 1973b; Kimberly, 1976; Kimberly & Evanisko, 1981). Thus, from an empirical standpoint, it is contended that due to a high degree of variation in the current average firm size dataset (outlined in Chapters-4 and 5), the use of log-transformed firm

size values is required. Thus, using raw firm size values can cause a high degree of distortion in the weighting scheme and adjustment factors. It is concluded that the inordinate variance in the current firm size dataset can be minimised (or eliminated) through log-transformations. Furthermore, the log-transformed values of firm size dataset better represent the curvilinear relationship between resource commitments and firm size, than the raw values of firm size (see Blau & Schoenherr, 1971; Camisón-Zornoza et al., 2004; Damanpour, 1992; Ettlie & Rubenstein, 1987; Kimberly, 1976; Kimberly & Evanisko, 1981).

Due to the theoretical and empirical viewpoints presented in this Section, log-transformed firm size values are used in the weighting scheme. In order to identify a suitable firm size metric for deployment, an overview of the firm size reporting practices is presented next.

3.3.3. Selection of an appropriate firm size metric

The measures of firm size employed in primary studies are very diverse (Camisón-Zornoza et al., 2004). The most common metrics of firm size in DC Theory and innovation literature are the average sales revenue of sampled firms (e.g., Drnevich & Kriauciunas, 2011; Grawe et al., 2009), and the average number of employees in firms (e.g., Atuahene-Gima, 2005; Danneels, 2012). Studies using sales revenue of firms as the firm size metric often report data in diverse currencies, contingent upon the national context of a study. For example, Drnevich and Kriauciunas (2011) reported average firm size as a natural log (i.e., log with base e) of firm revenue in millions of Chilean Pesos, whereas Grawe et al. (2009) reported firm size in million RMB (Chinese Currency Unit). The use of such diverse national currencies makes comparative analysis and computation of average firm size value for weights calculations difficult. One way of surmounting this difficulty is to express all currencies as a common currency such as the US Dollar or Euro. Nevertheless, currency exchange rate fluctuations render such a computation prone to errors.

By contrast, the other frequently employed measure (i.e., the number of employees in a firm) makes calculation of average firm size very reliable. Employee numbers is a direct and commonly adopted metric of firm size, with innovation studies characteristically using employee numbers (Camisón-Zornoza et al., 2004; Damanpour, 1992; Kimberly, 1976). Furthermore, the number of employees is supported in the literature as a popular metric for firm size due to its inherent validity (Child, 1973b).

The number of employees is generally reported either as an average (e.g., see Dai & Liu, 2009; Deeds et al., 1998), or as a frequency distribution with class intervals (e.g., see Grawe et al., 2009; Yam, Lo, Tang & Lau, 2011). Therefore, for two primary reasons: 1. employee numbers are the most frequently reported, and 2. employee numbers render themselves to reliable and direct comparisons across studies, the number of employees is selected to represent firm size in the current study.

3.3.4. The primacy of comparative measures

For computing weights and adjustment factors, effects measures are deemed inherently comparative regardless of whether they were or were not explicitly mentioned as such in incorporated studies. This is because innovation effects-oriented rating of PIC (for assessing the PIC-level possessed by a firm) is virtually impossible without a direct comparison with competing firms (the Table 2.2 in Chapter-2, presents examples of comparative qualifiers). This contention is explicitly recognised and employed in numerous studies (e.g., see Delgado-Verde et al., 2011; Durmuşoğlu & Barczak, 2011; Grawe et al., 2009; Hooley et al., 2005; Morgan et al., 2009; O'Cass & Ngo, 2012; Song et al., 2005). In other words, it is argued that an assessment of relative levels of PIC is enabled by a comparison of product innovation outcomes (as captured via effects measures), with the competing firms as a frame of reference. This argument is consistent with the observation made by Danneels (2012) concerning comparative measures, that they are highly popular with the research community. In a similar line of reasoning, Zahra and Covin (1993) assert that constructs relating to the field of strategic management are inherently comparative.

A central notion underlying the adjustments in reported correlations is that, due to the use of comparative effects measures and the oversight of productivity dimension, PIC levels are over- and under-estimated for large and small firms respectively. Hence, for incorporated studies focussing on Small and Medium Enterprises (SMEs), the PIC of the sampled firms is under-estimated with the exclusive employment of effects measures, as large firms have the advantage of greater resource inputs (see Lee et al., 2001; Panayides, 2006).

In the context of average firm size being used as a proxy for resource commitments, the degree to which PIC levels are over- or under-estimated is contingent upon the firm size disparities of incorporated studies. This is because PIC levels for large firms are over-estimated due to effects measures confounding PIC levels with greater resource inputs. Conversely, PIC levels for small firms are under-estimated in studies, as smaller firms are generally characterised by lesser resource inputs. This argument builds upon the core assertions concerning the oversight of the efficiency dimension of PIC in the empirical literature. Another premise underlying the weighting scheme is discussed next.

3.3.5. The similarity in firm size distributions

For computing adjustment factors, an implicit premise underlying the aggregation of studies conducted in different countries is that firm size distributions (FSDs) across different countries are largely similar. This assumption is important for the development of weighting scheme, given that the synthesised studies report results from several different countries. Ostensibly, due to data and/or resource constraints, conclusive research on FSD spanning multiple countries is yet to be undertaken and only (single) country-specific studies have been conducted. For example, Cabral and Mata (2003), and Pavitt, Robson and Townsend (1987) have focussed on FSDs in the UK and Portugal respectively. Importantly, considerable similarities in FSDs across countries have been identified in these studies (Cabral & Mata, 2003).

Additionally, 35 percent of incorporated studies in the current meta-analysis originate from a single country (i.e., 20 studies from the US, out of 57), supporting the premise that variations in FSD across firm samples are likely to be small in magnitude. Thus, small variations in FSDs are unlikely to be a source of large bias in the results of the current study. This argument substantiates the integration of firm samples originating from various countries in the weighting scheme. The contention also justifies the employment of average firm size deviations from the median, as the optimal yardstick for assessing the degree of relative resource advantage and disadvantage.

3.4. THE FRAMEWORK FOR THE EFFECT SIZE WEIGHTING SCHEME

The Figure 3.2 depicts the weighting scheme that involves the assignment of adjustment factors to reported correlations. In the Figure, ' $r(s)$ ' (with ' s ' denoting plurality) denotes reported correlations representing the relationship of interest, that are based on effects measures of PIC. Weights that factor in relative resource inputs are represented by ' $w(s)$ ' and the corresponding adjustment factors are denoted with $adjfac(s)$. Consequently ' $r(s)*adjfac(s)$ ' represents the assignment of adjustment factors, through the multiplication of reported correlations with corresponding adjustment factors.

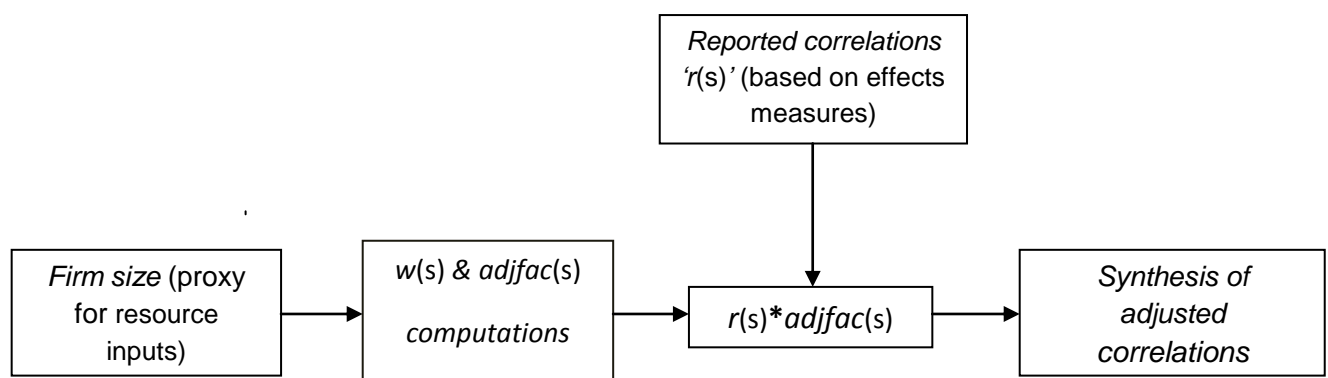


Figure 3.2: The weighting scheme for PIC–firm performance effect sizes

The calculation of adjustments factors is predicated on the rationale that the under- or over-estimation of PIC levels is contingent upon the extent to which the average-sizes of firms deviate from the central tendency of average firm size values (of all incorporated firm samples). This notion underlies the computational framework of the weighting scheme, and is described in the next Chapter with the help of a simplified hypothetical example.

The adjusted correlations obtained through the application of the weighting scheme, are expected to exhibit variation as also observed in reported (i.e., unadjusted) correlations. Variation in adjusted correlations points to the possibility of moderation effects, which was expected because incorporated studies were conducted in diverse national contexts. This warrants a detection of potential moderators of the PIC–firm performance relationship. Moderation analyses are a key component of virtually all meta-analyses, as researchers attempt to identify variables that potentially impact the relationships under investigation (e.g., Calantone et al., 2010; Cohen, 1993; Gooding & Wagner, 1985; Heugens & Lander, 2009; Read, Song & Smit, 2009; Sagie & Koslowsky, 1993).

The detection of potential moderators and assessment of their effects is a primary aim of the current research, as articulated through the third research question (presented in Section-1.2). Hence, testable hypotheses for the PIC–firm performance relationship and its potential moderators, namely, industry type, firm size and technological turbulence, are presented as follows.

3.5. MODERATION EFFECTS AND HYPOTHESES DEVELOPMENT

Identifying the moderation effects of a relationship is imperative for theory development (Schilke, 2014; Viswesvaran & Ones, 1995). Thus, the current study examines moderator variables so as to gain insights that could enable theoretical and empirical advancements of the DC Theory and innovation literatures. Importantly, attempts to empirically investigate boundary

conditions of DC Theory are relatively scarce and often report mixed results (e.g., Drnevich & Kriauciunas, 2011; Schilke, 2014; Wilhelm et al., 2015).

While highlighting the strengths of meta-analytic reviews, researchers affirm that meta-analyses enable the detection of moderator variables and estimation of their effects (e.g., Aguinis & Pierce, 1998; Hedges & Olkin, 1985; Hunter & Schmidt, 2004; Viswesvaran & Ones, 1995). Furthermore, scholars highlight the ability of meta-analyses to examine moderators that have not been investigated in primary studies (e.g., Damanpour, 1992; Guzzo, Jackson & Katzell, 1987). Meta-analyses also enable use of secondary data sources for estimating moderation effects (e.g., see Grinstein, 2008b). For example, several meta-analyses use country-specific scores for national culture dimensions to investigate the impact of national culture on the relationships of interest (e.g., Calantone et al., 2010; Kirca et al., 2005; Rubera & Kirca, 2012). These strengths of meta-analyses in assessing the moderation effects are relevant for the current study, as secondary data sources are used in this research for operationalising technological turbulence.

The two common approaches followed in meta-analyses for detecting moderators and ascertaining their effects are: 1. to hypothesise potential moderator variables before conducting data-analyses, and 2. to perform a test for moderation effects without hypothesised moderator variables (Borenstein et al., 2009). In the current study, the former approach (development of hypotheses prior to data-analysis) is adopted. This is because, based on a review of DC Theory and innovation literatures, it is possible to hypothesise potential substantive moderators influencing the PIC–firm performance relationship. In addition, it is the preferred approach in most meta-analyses (e.g., see Balkundi & Harrison, 2006; Crook, Todd, Combs, Woehr & Ketchen, 2011; Geyskens et al., 2009; Joshi & Roh, 2009; Li & Cropanzano, 2009; McEvoy & Cascio, 1987). The Figure 3.3 illustrates the meta-analytic model for investigating PIC–firm performance relationship and ascertaining its moderation effects.

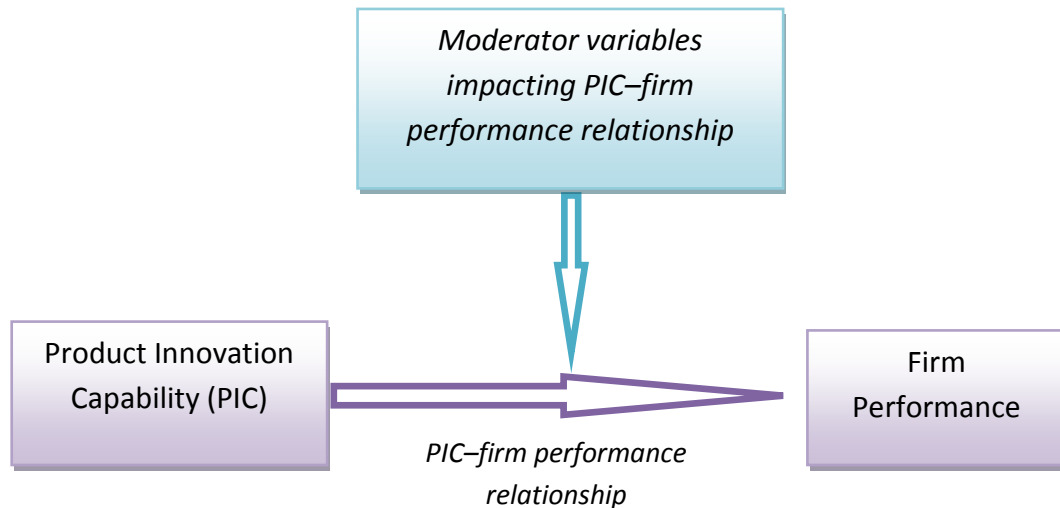


Figure 3.3: The PIC–firm performance meta-analytic model

Although the weighting scheme and adjustments to reported correlations constitute a salient component of the model, the Figure 3.3 is simplified to only encompass the core constructs in the study, as the weighting scheme is already outlined in the previous Section.

The first hypothesis of the study is centred on the direction and magnitude of the focal relationship, thereby directly addressing the second research question. As reviewed in the previous Chapter, PIC is said to *a priori* relate to firm performance so as to confer performance advantages on firms (see Eisenhardt & Martin, 2000; Schilke, 2014). This viewpoint is consistent with Schumpeter’s theory of profit-extraction according to which innovative products confer superior profits upon innovating firms, through the creation of advantages over rivals in the marketplace (Schumpeter, 1942; 1950).

While empirical studies frequently support the *a priori* contention that PIC–firm performance relationship is positive, many studies also report a negative correlation (e.g., Katila & Ahuja, 2002; Penner-Hahn & Shaver, 2005; Richard, McMillan, Chadwick & Dwyer, 2003). Furthermore, studies generally report varying degrees of strength between the two variables, necessitating a statistical synthesis for determining the direction and magnitude of the relationship. Thus, underpinned by the contentions presented here, the first testable hypothesis is formulated as:

Hypothesis-1 (H1): There exists a positive and significant relationship between PIC and firm performance.

H1 would be accepted or rejected on the basis of the value of summary effect size and associated statistics.

This study identifies potential moderators *a priori*, as mostly followed in meta-analyses that are conducted in management (e.g., see Calantone et al., 2010; Evanschitzky et al., 2012; Geyskens et al., 2009; Greenley, 1995; Grinstein, 2008a; 2008b; Liang, You & Liu, 2010; Phillips, 1998). Substantive moderators identified in the current study (i.e., industry type, firm size and technological turbulence), have been examined in a few primary studies and meta-analyses focussing on dynamic capability and innovation constructs (e.g., see Rubera & Kirca, 2012; Song et al., 2005). However, in light of conflicting findings, and the adjustments made to correlations in order to account for the productivity dimension of PIC, sub-group analyses can generate fresh insights into the moderation effects of the focal relationship.

3.5.1. Industry type

The impact of industry type on several relationships of interest has been studied in meta-analyses conducted in strategic management and marketing (e.g., see Grinstein, 2008b; Kirca et al., 2005; Krasnikov & Jayachandran, 2008; Vincent et al., 2004). Industry type is often categorised as manufacturing and services depending upon the nature of market offering, either products or services, respectively. Products and services have been highlighted in the literature to exhibit significant differences that are theorised by researchers (e.g., Damanpour, 1991; Zeithaml, Bitner & Gremler, 2006) to stem from several factors such as:

- 1) the core essence (intangibility versus tangibility) (Zeithaml et al., 2006),
- 2) greater variation and unpredictability in service production and delivery, as opposed to greater standardisation in manufacturing (Daft, 1983),
- 3) the nature of production and delivery processes (Zeithaml et al., 2006),

4) the proximity and intensive interaction between service providers and customers, unlike manufacturing (Mills & Margulies, 1980).

Damanpour (1991) opines that given the differences in the essence of services versus products, the antecedents of innovation and their relative significance would vary considerably between manufacturing and service industries. Some scholars maintain that differences between industry types often translate into greater opportunities for service firms to innovate, as many services are highly customised to suit customer demands (e.g., Cadogan, Sanna, Risto & Kaisu, 2002).

The empirical evidence about the influence of industry type on innovation and its association with firm performance is mixed and sometimes contradictory. For example, Jiménez-Jiménez and Sanz-Valle (2011) report a stronger innovation–performance relationship for manufacturing versus service firms in their study. On the other hand, Vincent et al. (2004), in their meta-analysis on the antecedents and consequences of innovation, report statistically non-significant differences between the effect sizes obtained from service versus manufacturing industries. The divergent results suggest that further investigation of the moderation effect of industry type is essential. In keeping with the discussion presented so far, a sub-group analysis of industry type as a potential moderator is undertaken in this study and it is hypothesised that:

Hypothesis-2 (H2): The relationship between PIC and firm performance is moderated by industry type.

3.5.2. Firm size

As discussed earlier (in Section-3.3.2.), the influence of firm size on various organisational variables has received a high level of research attention. In particular, the impact of firm size on innovation (and related constructs such as R&D capability) has been a subject of intense debate amongst innovation scholars (Rubera & Kirca, 2012), and firm size is also frequently posited to affect firm performance (Garg et al., 2003).

Schumpeter (1934; 1950) contends that large firms (as opposed to small firms) are the principal contributors of innovation. This contention, sometimes referred to as the Schumpeterian Hypothesis, has spurred substantial scholarly interest, but the research findings have often been conflicting (Acs & Audretsch, 1987; Cohen & Klepper, 1996). For example, studies have reported a positive (e.g., Aiken & Hage, 1971; Damanpour, 1992; Dewar & Dutton, 1986; Kimberly & Evanisko, 1981; Thornhill, 2006), statistically non-significant (e.g., Jervis, 1975), and sometimes even a negative association (e.g., Utterback, 1974) between firm size and innovation.

The literature is thus divided with regard to whether large firms or SMEs are more innovative, and whether size influences the ability of firms to secure performance benefits arising from innovative products. Researchers argue that the possession of specialised resources (such as knowledge) and capabilities are imperative for the creation of innovative products, and for securing consequent performance benefits (e.g., Hage & Aiken, 1970; Howell, Shea & Higgins, 2005; Schumpeter, 1934; Tsai, 2001). Large firms are more likely to be endowed with certain unique resources and capabilities such as the capacity to invest in and influence distribution channels (Mitchell, 1989), and the availability of skilled personnel for a timely and successful launch of new products. Large firms can also commit greater resource outlays for innovative activities such as finances and skilled human resources that may foster PIC and yield revenue-generating product innovations (see Rubera & Kirca, 2012). It is widely acknowledged in the literature that large firms benefit from economies of scale, that facilitate reduction in the cost of operations (Gaba, Pan & Ungson, 2002). Additionally, innovative products from large firms are perceived to carry reduced purchase risk by prospective consumers as a consequence of their (often) superior reputation and longevity (Chandy & Tellis, 2000). The reduced risk perception of purchasing innovative products from large firms potentially facilitates the trial and acceptance of new products in targeted market segments.

Furthermore, dynamic capabilities are posited by several proponents to be idiosyncratic (e.g., Makadok, 2001; Teece et al., 1997), and large firms are

said to possess greater idiosyncrasies and complexities in their processes (Krasnikov & Jayachandran, 2008). Idiosyncrasies reflect uniqueness in organisational systems, routines and processes that potentially make them highly inimitable by competing firms. This suggests that PIC and the association between PIC and firm performance could be stronger for large firms.

On the other hand, SMEs are said to be more agile and flexible (e.g., Damanpour, 1996; Rogers, 2004; Verhees & Meulenbergh, 2004). Such characteristics enable many SMEs to yield successful innovations despite resource constraints (Rosenbusch et al., 2011; Thornhill, 2006). On the other hand, large firms are likely to develop inertia that may impede their ability to respond to changing conditions (Boeker, 1997). Due to the posited greater responsiveness of SMEs, they may benefit from innovations that cater to specific market niches for a protracted duration, versus their larger counterparts (Rosenbusch et al., 2011). These characteristics of SMEs are expected to enhance PIC levels and strengthen the PIC–firm performance relationship. However, Jiménez-Jiménez and Sanz-Valle (2011) have empirically deduced a stronger association between innovation and performance for large firms, rather than for SMEs. Furthermore, in assessing moderation effects of firm size, Rubera and Kirca (2012), in their meta-analysis, reported mixed findings with regards to the association of innovativeness with different performance metrics, for large firms and SMEs.

Based on the preceding discussion, it is argued that empirical findings concerning firm size as a moderator of the relationship between innovation constructs (such as PIC) and firm performance are inconsistent. This necessitates further examination of the moderation effects of firm size. It is expected that an investigation of the moderation effect by firm size, on the PIC–firm performance relationship, will yield novel insights and enable a better understanding of the relationship.

For examining potential moderation by firm size, the variable will be dichotomised as either large firms or SMEs, as mostly followed in the literature (e.g., Rosenbusch et al., 2011). This dichotomisation (i.e., large

firms versus SMEs) enables a sub-group analysis of firm size on the focal relationship. Therefore, a testable moderation hypothesis is presented as:

Hypothesis-3 (H3): The PIC–firm performance relationship is moderated by firm size.

It should be noted that the deployment of firm size as a proxy for resource inputs is entirely extraneous to the firm size's treatment as a potential moderator. In the former, the firm size acts as a 'substitute' for lack of data on resource inputs, which is required for the weighting scheme, whereas in the latter case, it is modelled as a moderator influencing the relationship under investigation. The two cases are independent of each other and there is no possibility of any 'cross-effects'.

3.5.3. Technological turbulence

Researchers strongly encourage a rigorous examination of the moderating influence that technological turbulence potentially exerts on various relationships (e.g., Krasnikov & Jayachandran, 2008), as sometimes attempted in the literature (see Song et al., 2005). However, such investigation of moderation by technological turbulence is scant and a meta-analytic examination can generate useful findings. Thus, technological turbulence warrants an examination as a potential moderator for the focal relationship, as outlined in the previous Chapter.

Technological turbulence is asserted to be the primary driver of market dynamism in the current business environment and therefore, also used in this study as a proxy for the broader market dynamism construct (e.g., see Day, 2011; Thornhill, 2006; Wilhelm et al., 2015). A discussion of potential moderation impact by market dynamism on the focal relationship, and the appropriateness of treating technological turbulence as a proxy for market dynamism were presented in Section-2.4. Hence, for the sake of brevity, a detailed discussion is not provided here.

Proponents of DC Theory ascribe a critical role for dynamic capabilities in market/environmental conditions that are characterised by moderate to high market dynamism (e.g., Eisenhardt & Martin, 2000; Makadok, 2001; Teece et al., 1997; Winter, 2003). Divergent findings concerning the moderating influence of market dynamism on the association between dynamic capabilities and firm performance has been reported in empirical studies (e.g., Drnevich & Kriauciunas, 2011; Schilke, 2014). Hence, by inferential reasoning, an examination of the moderation effect of technological turbulence is also expected to generate insights into the influence of market dynamism on the PIC–firm performance relationship (see Cohen, 1981; Zieffler, Garfield, Delmas & Reading, 2008). Therefore, a moderation analysis for technological turbulence is undertaken in this research, and a hypothesis is formulated as:

Hypothesis-4 (H4): The PIC–firm performance relationship is moderated by technological turbulence.

All moderation hypotheses presented in this Section will be tested meta-analytically through sub-group analyses. The analyses will provide results concerning the statistical significance of moderation effects, which would enable the acceptance or rejection of the hypotheses presented here. A summary of this Chapter is provided next.

3.6. CHAPTER SUMMARY

The Chapter presented a novel meta-analytic framework. An effect size weighting scheme was described that is central to the proposed framework and which attempts to comprehensively operationalise PIC, in this study. The weighting scheme enables relative resource inputs to be factored in, concurrently with product innovation outcomes. This is accomplished through undertaking adjustments in the reported effect sizes. The adjustments are required in order to capture the relative efficiency of resource utilisation by firms, an overlooked dimension of PIC that has resulted in the construct

validity problem. Additionally, potential moderator variables were outlined in the Chapter and their effects on the focal relationship were hypothesised. The moderator variables presented have been subjected to empirical assessment in the innovation and DC Theory literatures but often yielded mixed results, thereby warranting further investigation.

The next Chapter describes the meta-analytic model adopted, computational procedures for the weighting scheme and summary effect size, sub-group and sensitivity analyses, and the file drawer problem. The criteria for study inclusion and a protocol for study coding are also outlined in the following Chapter.

CHAPTER FOUR

RESEARCH DESIGN AND METHODOLOGY

4.1. INTRODUCTION

The second Chapter presented a review of the DC Theory and innovation literatures and assessed the construct validity of PIC via theoretical triangulation. The Chapter identified a critical deficiency in PIC measurement and also established the requirement for synthesising empirical research concerning the relationship of PIC with firm performance. Subsequently, Chapter-3 presented a meta-analytic model that aims to bridge the identified construct validity gap of PIC via statistical aggregation. The key component of the meta-analytic framework is the unique effect size weighting scheme, which entails the use of the average size of sampled firms as the proxy for relative resource allocations. Potential moderators were also hypothesised in the previous Chapter to assess moderation effects on the relationship of interest.

The current Chapter provides details of the research design and methodological procedures. The Chapter commences with an outline of alternative meta-analytic models (and reasons for selecting random-effects model in this research), choice of effect size metric and the computational approach adopted for the PIC–firm performance meta-analysis. The procedures for calculating weights and adjustment factors, in accordance with the effect size weighting scheme is then presented. The use of firm size as a proxy for resource allocations and adjustments to correlations are explained with a hypothetical example. Hypothetical dataset comprising only five studies was chosen for illustrating the computational framework in order to simplify the presentation of the procedures deployed for the weighting scheme. The hypothetical data contained whole numbers that potentially facilitated understanding of a complex mathematical undertaking. The real dataset

comprising a much larger number (i.e., 57 studies) and fractions (or decimals) could impede the understanding of procedures.

The methods and criteria used for data collection such as those for (primary) study inclusion, the study coding protocol, the coding of moderators, the corrections for study imperfections and summary effect size computation are subsequently discussed. The Chapter concludes with a description of the methods incorporated in this meta-analysis for outliers and sensitivity analyses, and the file drawer problem.

Meta-analyses frequently entail certain trade-off decisions to overcome constraints, such as data unavailability due to unreported reliability estimates (see Geyskens et al., 2009). Such decisions, as implemented in the current study, are presented alongside a discussion of pertinent meta-analytic practices and the theoretical contentions that underlie them.

4.2. FUNDAMENTAL DECISIONS CONCERNING STUDY DESIGN AND METHODOLOGY

Decisions concerning meta-analytic design and methodology were made and implemented after a comprehensive examination of research practices and scholarly recommendations (e.g., Aguinis et al., 2011; Geyskens et al., 2009; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001). A very high level of replicability is argued by researchers to be amongst the principal strengths of meta-analytic reviews and thus “procedures must be spelled out in detail so that meta-analyses are fully replicable” (Aguinis et al., 2011: 1041). Given the importance of explicitly describing procedural details and decisions in order to enhance replicability of the current study, methodological decisions and their underlying rationales are discussed next.

4.2.1. The selection of Random-effects (RE) model

The nature of meta-analytic findings, such as summary effect sizes and moderation effects are to a certain degree, contingent upon the choice of meta-analytic model (Aguinis et al., 2011). Consequently, the careful selection of an appropriate model for the PIC–firm performance meta-analysis was important. The most commonly used models of meta-analyses are the random-effects (RE) and fixed-effect (FE) models and the two models differ in the core assumptions that underpin them. Under the FE model, the underlying premise is that the true effect size is the same for all the studies being synthesized. This assumption implies that observed variation in the reported effect sizes is due to sampling error (Aguinis et al., 2011; Borenstein et al., 2009; Hedges & Olkin, 1985). On the other hand, the RE model is based on the premise that true effect size varies from one study to another (Aguinis et al., 2011; Borenstein et al., 2009; Hedges & Olkin, 1985). This means that the construct-level relationship is considered to substantively differ amongst studies in an RE model. Due to the fundamental premises that underlie the two models, the choice of the appropriate model hinged on the nature of primary studies and the specific aims and scope of the present meta-analysis.

A RE model is virtually always a superior choice out of the two models in organisational science research when incorporated studies are passive observational, rather than based on randomised controlled trials (Aguinis et al., 2011; Borenstein et al., 2009). It was observed that studies investigating PIC–firm performance relationship use passive observational designs and not randomised controlled trials. Aguinis et al. (2011: 1035) state that FE “meta-analysis could occur in the biological, medical and health sciences” and that such a meta-analysis are “difficult to justify in organisational research”. Similarly, Borenstein et al. (2009) affirm that deployment of FE model should be undertaken only when the following conditions are met: 1. the studies being synthesized are functionally identical and 2. only a specific population is under investigation. The very unlikely event of the independent primary studies satisfying these two conditions in DC Theory and innovation research is accounted for in the RE model which allows for variation in the true effect

size (see Borenstein et al., 2009). Additionally, the RE model enjoys widespread acceptance in social science research and most meta-analytic reviews published in management employ this model (e.g., see Zablah, Franke, Brown & Bartholomew, 2012; Read et al., 2009). Thus, a RE model was chosen for conducting the meta-analysis in the current study.

4.2.2. The choice of effect size metric

An “effect size” represents the relationship of interest in terms of its magnitude and direction, and its metrics take diverse forms such as standardized and unstandardized mean differences, response ratios, risks and odds ratios and Pearson’s correlation coefficients. The metrics most commonly used in meta-analyses conducted in social sciences are the standardised mean difference and correlation coefficient (Borenstein et al., 2009). Empirical studies in management generally report correlation coefficients, or metrics such as Chi-square (χ^2), *t*-statistic and univariate-*F*, that can then be converted into correlation coefficients for representing bivariate relationships, such as between PIC and firm performance. Pearson’s correlation is appropriate for this meta-analysis, as the PIC and firm performance metrics are likely to be normally distributed and the two variables are assumed to have a linear relationship. Pearson’s correlation is the ‘default’ choice for meta-analyses conducted in management (e.g. Büschgens et al., 2013; Camisón-Zornoza et al., 2004), as the primary studies typically use this metric for reporting results. This choice is further discussed below.

An important guideline concerning the selection of the most appropriate effect size metric is to synthesize the most commonly used effect size metric in the incorporated studies that assess the relationship under investigation (Lipsey & Wilson, 2001). The selection of the most commonly used effect size metric facilitates data extraction and minimizes the requirement for cross-computation between alternative metrics. Additionally, a common effect size metric enables direct comparison across studies (Lipsey & Wilson, 2001). In light of these contentions, the Pearson correlation coefficient is the chosen effect size metric for the current study.

4.2.3. Computational approach

The usual practice is to either adopt the Hunter-Schmidt computational procedure when the effect sizes being synthesized are correlation coefficients or the Hedges et al. procedure when the effect sizes are standardized mean differences (Aguinis et al., 2011; Borenstein et al., 2009; Hedges & Olkin, 1985). The choice of correlations as effect sizes in the present study favours the Hunter-Schmidt approach. Furthermore, Aguinis et al. (2011) contend that the Hunter-Schmidt approach is appropriate if the research aims also involve understanding boundary conditions (in addition to the summary effect size computation), as this approach accounts for methodological and statistical *artifacts*. The term artifact refers to errors inherent in empirical findings that arise from study design and methodological imperfections (Hunter & Schmidt, 2004). This approach enables researchers to undertake corrections for methodological and statistical errors in incorporated studies (Aguinis & Pierce, 1998), thereby facilitating calculation of a superior summary effect size (Hunter & Schmidt, 1990).

Most meta-analyses employ the Hunter-Schmidt approach and its popularity underscores its acceptance in the scholarly community (e.g., see Crook et al., 2008; Geyskens et al., 2006; Kirca et al., 2011). Therefore, the Hunter-Schmidt procedure was employed in this research for investigating the PIC–firm performance relationship.

4.3. THE COMPUTATIONAL PROCEDURE FOR THE WEIGHTING SCHEME

As previously highlighted in Chapters-2 and 3, the unavailability of resource input data alongside output-oriented data (via effects measures) for operationalising PIC was a severe constraint for overcoming the validity problem. The proposed solution to the problem was the formulation and

deployment of an effect size weighting scheme, as theoretically outlined in Chapter-3. The scheme is argued to enable the concurrent consideration of both resource inputs and effects measures, thereby accounting for the productivity dimension of PIC.

It was essential to ensure that adjustment factors did not yield an insubstantial cumulative effect on the summary effect size through the aggregation of adjusted correlations. This is because any cumulative effect of assigning adjustment factors to individual correlations could eventuate in a summary effect size that may misrepresent the relationship under investigation. A solution to this potential pitfall is the use of a suitable measure of central tendency for the firm size dataset, and the determination of deviations of the average firm sizes from the central tendency value. It is contended that by computing deviations from the central tendency value, the cumulative effect of aggregating individually adjusted correlations would not lead to distortions in the summary effect size. As discussed in the previous Chapter, the average number of employees in sampled firms is the preferred firm size metric for estimating the relative resource inputs. The selection of a suitable central tendency measure for firm size (i.e., the number of employees) is outlined next.

4.3.1. The choice of central tendency measure

There are several commonly employed central tendency measures such as the arithmetic mean, median, mode, harmonic and geometric means. Each measure has associated advantages and disadvantages, which will not be discussed here for the sake of parsimony. After carefully weighing the appropriateness of each central tendency measure and the nature of the average firm size dataset, the *median* was selected as the most appropriate choice. The median was chosen for calculating the central tendency of average firm size dataset as it is unaffected by the presence of extreme values in the dataset (Malhotra, 2014).

The median value of the dataset was interpreted as a *baseline* level and each individual average firm size was computed as a fraction (i.e., ratio) of this median value. In this case, the ratios represented deviations from the median.

The underlying rationale behind expressing each average firm size as a ratio of median was to devise a system of weighting that calibrates the average firm size of each study relative to other average firm sizes in the dataset. This ensured that the relative resource allocations made by firms towards product innovation are captured through a procedure involving the use of a suitable central tendency metric and relative firm size. To summarise, this step in the procedure involved the average firm size of each incorporated study to be expressed as a ratio of the median of the firm size dataset. The individual study-specific weights thus yielded, are further explained in the following section.

4.3.2. Computation of study-specific weights

The computational steps of the weighting scheme are illustrated by a hypothetical example shown in Table 4.1. The Table serves to simplify explanation of the procedures undertaken in the current study for the actual data analysis. In order to account for the relative resource commitments, the ratios of average firm sizes to the median value were computed and labelled as weights. In other words, weights are the firm sizes expressed as ratios of the median, calculated and presented in the Table 4.1. These weights can also be understood as the average firm size of sampled firms in a particular study, relative to the average firm size of all the sampled firms. It is important to note that firm size as a proxy for resource allocations was converted via log transformations in the actual dataset, rather than using raw values, due to the curvilinearity rationale (discussed in Chapter-3). Nevertheless, the latter (i.e., raw values) are used in the following Table for the purpose of illustration, as they are more intuitive (compared to log values) and facilitate a better understanding of the computational procedures and underlying rationales.

Table 4.1: Information reported in primary studies and weights computation (hypothetical data with the median of number of employees=300)

	<i>Reported effect sizes (correlation coefficients)</i>	<i>Reported 'average firm size' (no. of employees)</i>	<i>Weights ('average firm size' / median)</i>
Study-A	0.20	100	$100/300= 0.33$
Study-B	0.10	200	$200/300= 0.67$
Study-C	0.50	400	$400/300= 1.33$
Study-D	0.40	500	$500/300= 1.67$
Study-E	0.30	300	$300/300=1.0$

In the Table, as Study-A has the smallest average firm size of 100 employees, its corresponding weight (as represented through a ratio of average firm size to the median) is the lowest. By contrast, Study-D receives the highest weight via the same procedure.

Deployment of either logarithm of base-10 or base-e (also called common or natural logarithm, respectively) in the weighting scheme was considered, as both methods are often used in research. The common logarithm was ultimately employed for computing adjustment factors, as the two methods are expected to yield virtually identical results. Indeed, Gujarati (2006: 288) states that, “there is a fixed relationship between the common log and natural log...[thus] it does not matter whether one uses common or natural logs”. The final computational step in the scheme, involving calculation of adjustment factors and their assignment to effect sizes, is explained next.

4.3.3. Assignment of adjustment factors to effect sizes

Hunter and Schmidt (2004), and Schmidt and Hunter (1996) have demonstrated that through the employment of a statistical correction formula, the problem of imperfect construct validity can be eliminated. Thus, a

correction formula was employed to address the gap identified in the validity of PIC. A simple calculation enables generation of adjustment factors (based on weights) that can be assigned to corresponding effect sizes (correlations). The assignment of adjustment factors to correlations is argued to account for the relative resource inputs by the sampled firms, thereby incorporating the productivity dimension of PIC. In accordance with the contentions made by Hunter and Schmidt (1990; 2004) and Schmidt and Hunter (1996) for correcting measurement errors, the square roots of weights were obtained using the following disattenuation formula:

$$r_{x(t) y(t)} = r_{xy} / (r_{xx} r_{yy})^{1/2} \quad \text{Formula-4.1}$$

where, 'x' and 'y' are the IV and DV respectively. $r_{x(t)y(t)}$ and r_{xy} are the true correlation (for the construct level relationship) and the observed correlation respectively. r_{xx} and r_{yy} are the reliabilities of the IV and DV respectively. The exponent ' $1/2$ ' represents the square root of the denominator. (Schmidt & Hunter, 1996: 201)

The disattenuation formula has also been referred to as the formula for "Hunter and Schmidt's (1990) construct validity corrections" (Read et al., 2009: 579). This formula is the default choice for correcting errors arising out of imperfections in measurement (see Schmidt & Hunter, 1996; Hunter & Schmidt, 1990). Therefore, the formula was deployed in the current study for making adjustments to reported correlations. It can be contended that the procedure for correlation adjustments presented here is analogous to the corrections for reliability errors, as adhered to in virtually all meta-analyses in social sciences (e.g., Brinckmann et al., 2010; Grinstein, 2008a; 2008b; Joshi & Roh, 2009; Sarooghi, Libaers & Burkemper, 2015).

The square roots of firm size derived weights, labelled adjustment factors, were therefore used for obtaining adjusted correlations. The calculation and assignment of adjustment factors is presented in Table 4.2. For the sake of continuity and simplicity, the hypothetical data comprising reported correlations, average firm sizes and computed weights used in Table 4.1 is carried over to explain the assignment of adjustment factors in Table 4.2. The Table shows the derivation of adjustment factors from corresponding study-specific weights.

Table 4.2: Adjustment factors and adjusted correlations (hypothetical data)

	<i>Weights (average firm size/median)</i>	<i>Adjustment factors [(Weight)^{1/2}]</i>	<i>Adjusted correlations (Correlations/Adjustment factors)</i>
Study-A	0.33	0.57	0.2/0.57= 0.35
Study-B	0.67	0.82	0.1/0.82= 0.12
Study-C	1.33	1.15	0.5/1.15= 0.43
Study-D	1.67	1.29	0.4/1.29= 0.31
Study-E	1.00	1.00	0.3/1.0= 0.3

It should be noted that, as also shown in the Table 4.2, the revisions in the reported effects sizes were inversely proportional to the square roots of their corresponding weights. In other words, the effect sizes reported in studies with firm sizes smaller than the median increased in magnitude, and this increase in the effect size was proportionate to the extent by which the average firm size reported in the study deviated from the median. Conversely, the effect sizes reported in studies with firm sizes greater than the median decreased in magnitude.

For example, the effect size for Study-A was revised upwards, as a result of the average firm size of this study being the least, even though the computed weight for the study is the smallest. Consequently, the effect size of Study-A underwent the highest escalation in value from 0.2 to 0.35 as this study has the smallest average firm size. Study-D on the other hand, with the highest average firm size, had its correlation revised downward from 0.4 to 0.31. As already stated, the actual revisions in correlations were much lower in magnitude than the values presented here as log-transformed values were used in the study and not raw data. The actual values of adjustment factors used for modifying correlations, and their calculations from respective weights, are presented in Appendix-6. Although, the data (weights, adjustment factors,

etc) in the Tables 4.1 and 4.2 are not the same as contained in Appendix-6, they are conceptually identical. This is due to the deliberate use of hypothetical data for the purpose of illustration in the Tables 4.1 and 4.2.

The fundamental rationale for devising the effect size weighting scheme was to systematically factor in the relative resource inputs (towards product innovation activities) of sampled firms, as reflected by their size. Thus, the scheme accounts for the unspecified PIC dimension concerning the efficiency with which the resources committed to product innovation are utilised. As theorised earlier in previous Chapters, capturing the productivity dimension enables a comprehensive operationalisation of PIC. Consequently, a superior estimate of the true PIC–firm performance relationship can be obtained.

If all the firms in the dataset were of equal size (a near-impossible condition), the weights and adjustment factors would have a value of one and their assignment would not create any upward or downward revision in effect sizes. In other words, if all the sampled firms in the incorporated studies could be characterised by identical levels of resource commitments, effects measures solely would prove adequate for capturing PIC. Since this condition can never actually be encountered, the assignment of adjustment factors to the effect sizes was necessary. Not all incorporated studies reported firm size data and this was a constraint in the assignment of adjustment factors to all effect sizes in the dataset.

4.3.4. Unreported average firm size values

The average firm size was unreported in 20 studies (e.g., Penner-Hahn & Shaver, 2005; Tatikonda & Montoya-Weiss, 2001). Repeated attempts were made to contact the authors of the studies not reporting average firm size, but efforts yielded only three responses. The authors of 17 studies (from the total of 20) did not respond to email requests and to subsequent reminders for soliciting average firm size data. Three responses from Shoenecker T., Fabi B. and Sok P., were received but the average firm size of only one study, namely, O'Cass and Sok (2013b) could be provided by the authors. The other two authors no longer had firm size details in their databases.

Consequently, 38 studies in total (out of the 57 incorporated), representing two-thirds of the dataset, were useable in computing weights. Due to the uniqueness and novelty of the proposed weighting scheme, no precedents or guidelines exist in the literature for resolving the issue of missing average firm size data. However, a decision was made to include such studies by following the generic guidelines proposed by Malhotra (2014), and the practices followed in the meta-analytic literature. Amongst the various options usually available to the researchers for overcoming the problem of missing data, replacing missing average firm size data with the median of reported firm sizes was deemed appropriate (see Malhotra, 2014). Stated differently, the reason for assigning the median value to missing firm size values was that the assignment of the median (rather than nothing) would yield a summary effect size that better represents the true relationship. This decision is analogous to the substitution of missing reliability estimates with the mean (either simple or weighted) of reported reliabilities, as generally adopted in meta-analyses (e.g., Kirca et al., 2005; Geyskens, Steenkamp & Kumar, 1998; Stam, Arzlanian & Elfring, 2014; Kellermanns, Walter, Floyd, Lechner & Shaw, 2011; Sivasubramanian et al., 2012).

Therefore, due to the unavailability of firm size data from 19 studies, the effect sizes extracted from them were consequently not weighted. Not assigning weights to the effect sizes essentially means that due to the unavailability of average firm size, the studies with unreported firm sizes were considered to have average firm size equal to the median. The median of (raw) average firm sizes reported in incorporated studies was 103.5 (number of employees).

In cases where the firm size was reported in the form of a frequency distribution in a study, the formula used for determining the central tendency of firm size was:

$$\text{Median} = L + i * [N/2 - \text{c.f. (previous)}] / F \quad \text{Formula-4.2}$$

Where, F= frequency of median class, N= Total number of sample firms for a specific study, c.f. (prev) = cumulative frequency of the class preceding the median class, L= Lower limit of the median class, i = median class interval, – (en dash) represents subtraction and the asterisk (*) represents multiplication

The median computed using the method is the central tendency of the firm size frequency distribution of a given study, and is different from the median of average firm sizes employed in the weighting scheme. The latter is the median of the data comprising all the reported average firm sizes from incorporated studies. For one study, namely, Guan and Ma (2003), that reported separate average firm sizes for mutually exclusive categories of sampled firms, a weighted average was computed to obtain a single representative firm size value.

A search of empirical literature was undertaken for locating suitable studies for inclusion into the dataset. Studies fitting into the scope of the current meta-analysis and providing the relevant data were identified and coded in accordance with the procedures outlined next.

4.4. DATA COLLECTION

A keyword search to obtain data for the meta-analysis was conducted through online databases. Databases such as ABI/INFORM, Proquest, Emerald, Kluwer, EBSCO Business Source Complete and JSTOR, were searched with the keywords: 1. product innovation capability, 2. innovation capability, 3. R&D capability, 4. dynamic capabilit* (the asterisk '*', as a suffix encompasses singular and plural forms i.e., capability and capabilities), and 5. firm performance. These databases are most commonly searched for the identification of potentially relevant studies in meta-analyses (e.g., see Grinstein, 2008b, Kirca et al., 2005; Leuschner, Charvet & Roger, 2013; Zablah et al., 2012). They also have amongst the largest repository of published journal articles and collectively provide a comprehensive source of empirical studies.

Additionally, journals regularly publishing research articles relating to PIC, dynamic capabilities, innovation and innovativeness were manually searched for the period 01.01.1990 onwards (the choice for this time span is explained in the next Section). These included: *Journal of Product Innovation*

Management, European Journal of Innovation Management, Academy of Management Journal, Strategic Management Journal, Journal of Intellectual Capital, Entrepreneurship and Innovation, and Industrial Marketing Management. Furthermore, a process termed *ancestry search* was used in which the reference lists of articles relating to PIC and R&D capability were scrutinised to identify potentially usable studies for incorporation.

In addition to data collection from published studies, unpublished studies are generally required to be included in meta-analyses to minimise *publication bias*. The publication or availability bias (also labelled the file drawer problem) refers to the problem that published studies may only include those which have found statistically significant results, thus restricting the range of data for synthesis in a meta-analysis (discussed further in Section-4.8 of this Chapter). Therefore, in an endeavour to minimise this problem, a request for unpublished studies investigating PIC (and overlapping constructs) and firm performance were posted on the Academy of Management (AoM) Listservs. Although no unpublished study could be procured through the AoM Listservs request, it yielded two additional published studies, namely, Kuckertz Kohtamäki M. and Körber (2010) and Sirén et al. (2010), from the subscribers. These two studies were thus incorporated in the dataset. The two studies did not appear in the earlier online database search as their titles and abstracts did not contain relevant search keywords (enumerated earlier in this Section). This indicated that notwithstanding a thorough search, some usable studies in the literature probably remained unaccounted for. Nonetheless, any unaccounted for studies are unlikely to affect the current analysis adversely as a sufficient number of studies are included in the dataset. The adequacy of incorporated study numbers and the criteria for their (i.e., studies') inclusion in the PIC–performance meta-analysis are discussed next.

4.4.1. Study inclusion criteria

As recommended by Lipsey and Wilson (2001), the selection of studies was performed so as to ensure that only relevant studies were incorporated.

Studies were considered suitable for inclusion if they satisfied the following criteria:

- 1) Studies must report effect sizes for the PIC–firm performance relationship, and size of the firm samples examined.
- 2) Studies must measure constructs at the firm-level (and not product or product-line levels). This criterion ensures uniformity of data, and identical level of analysis (Hunter & Schmidt, 1990).
- 3) Studies must be independent from each other. This criterion implies that the studies should have investigated independent firm samples for reporting an effect size metric (Lipsey & Wilson, 2001).
- 4) The studies must be published after 01.01.1990 for inclusion, and deploy effects measures for operationalising PIC. The year chosen (1990) coincides with the emergence of DC Theory (see bibliometric review by Vogel & Güttel, 2013). This also spans a period of time consistent with several other meta-analytic reviews (e.g., see Crook et al., 2011; Joshi & Roh, 2009; Liang et al., 2010).

Consequent to the assessment of studies against the incorporation criteria, 169 studies from 226 identified were not included due to reasons, such as, the measures for PIC (and overlapping constructs) in the studies were not in correspondence with the effects measures adopted in the current study. This was important to ensure that effects measures were not confounded with resource-input measures and that PIC operationalisation was consistent across incorporated studies.

An important decision in data collection concerns the critical mass or minimum number of studies that must be included to enable a meaningful data-analysis. Although there are no heuristics to determine the optimal number of studies to be included in a meta-analysis, researchers often

endeavour to collect the maximum possible numbers to enhance the statistical power of the analysis (e.g., see Kirca et al., 2011; Kirca et al., 2005). Thus, for the current study, 57 studies (representing 58 independent firm samples) were procured and the total number of effect sizes reported in the incorporated studies was 81. The sum of the sample sizes examined in all the incorporated studies was 13,911 firms.

Several considerations, such as the nature of primary studies, the effect size metric, time and resource constraints and research objectives, determine study numbers (Lipsey & Wilson, 2001). It was observed that the number of studies incorporated in meta-analyses (in management) can vary considerably. For instance, Li and Cropanzano (2009) include 12 studies, whereas Zablah et al. (2012) include 291 studies. After an extensive review, it was observed that a large majority of meta-analyses conducted in areas such as innovation, marketing and strategic management incorporate studies that number between 20 and 60 (see Appendix-3). The mode and the median of study numbers in these meta-analyses are 46 and 39 studies respectively.

Rosenbusch et al. (2011) affirm that the synthesis of 42 studies in their meta-analysis was sufficient for a meta-analytic assessment. In support of the adequacy of 42 studies for examining the innovation and firm performance association, Rosenbusch et al. (2011: 448) state that (the number of collected studies) “represent a strong empirical base for a meta-analysis”. Study numbers in the vicinity of 42 studies, as in Rosenbusch et al. (2011), have been synthesised most frequently, as shown in Appendix-3. For example, 47 studies were aggregated in Brinckmann et al. (2010); 48 in Read et al. (2009); 39 in both Joshi and Roh (2009) and Leuschner et al. (2013), and 50 in a recent meta-analysis conducted by Verma, Sharma and Sheth (2015). In keeping with the numbers of studies aggregated in previous meta-analyses, a synthesis of studies in the neighbourhood of the median (i.e., 39 studies) was deemed sufficient for the current meta-analysis. Nevertheless, intensive efforts that yielded 57 studies were undertaken to obtain a greater number of studies than the median, in order to enhance the statistical power of the analysis.

The inclusion rate of studies in the current meta-analysis is 25.22 percent (i.e., 57 studies out of the 226 studies examined) which is less than the inclusion rate observed for most meta-analyses (e.g., Grinstein, 2008b; Kirca et al., 2005; Stam et al., 2014). The inclusion rate was computed as the number of studies synthesised in the meta-analysis expressed as a percentage of the number of studies examined. Table 4.3 presents the inclusion rate for several meta-analyses conducted in fields such as marketing, strategic management, innovation and organisational behaviour. The data in the Table suggest that generally, between two-fifths (40%) to three-fourths (75%) of the total studies accumulated via manual and electronic (online databases) search are expected to yield usable effect sizes for inclusion.

The low inclusion rate in the current study can be largely ascribed to the very selective approach that stipulated inclusion of effect sizes based solely on effects measures of PIC. A considerable number of studies operationalising PIC (and overlapping constructs) were observed to employ resource input measures. Such studies constituted a substantial proportion (approximately one-half) of the total number of studies examined, and were excluded from the dataset. Only the studies using effects measures (alongside other relevant PIC measures as discussed in Chapter-2) were incorporated for analysis.

Table 4.3: Study inclusion rates

<i>Study [Author(s), year]</i>	<i>Inclusion rates</i>
Brinckmann et al. (2010)	39%
Brown and Peterson (1993)	66%
Grinstein (2008b)	71%
Henard and Szymanski (2001)	59%
Joshi and Roh (2009)	41%
Kirca et al. (2005)	61%
Leuschner et al. (2013)	75%
Stam et al. (2014)	40%
Szymanski et al. (1993)	63%

Some studies (e.g., Li & Atuahene-Gima, 2002) were not incorporated as they examined the same firm sample as other publications by the same authors. This ensured that the same firm sample was not considered more than once in the meta-analysis, thereby eliminating over-representation. By contrast, a single study, namely, Lööf and Heshmati (2006), reported effect sizes for two separate firm samples. Thus, two usable effect sizes (i.e., one effect size for each sample) could be extracted from this single study.

A few studies that were *prima facie* useful could not be coded as they were in language other than English. For example, a study by Lavia, Otero, Olazaran and Albizu (2011) has been published in Spanish. Due to the constraints of time and high financial expense involved in engaging the services of a professional translator, such studies were dropped from consideration. This constraint has been highlighted in other meta-analyses as well, and these meta-analyses also incorporated studies published only in English (e.g., Damanpour, 1991; 1992). A description of the coding for studies meeting the incorporation criteria is presented next.

4.4.2. Study coding for data extraction

Studies meeting the incorporation criteria were subjected to data extraction by formulating a study coding protocol. A study coding protocol is a tool that enables meta-analysts to obtain pertinent data from empirical studies. Coding of studies is analogous to interviewing human respondents through a survey questionnaire. Hence, “subjects” in study coding are research papers that meet the incorporation criteria, rather than individuals who might meet the sampling criteria in survey research.

Researchers generally have the discretion of determining the appropriate definitions and scope of variables that are under investigation (Lipsey & Wilson, 2001). This essentially affords a degree of freedom to the researcher to determine whether it is suitable to identify IVs and DVs at a broader or narrower level, to ensure congruence with the aims of the meta-analysis (Lipsey & Wilson, 2001). Therefore, the variable definitions, data requirements

and specific aims of the current meta-analysis (as discussed in the thesis so far), informed the development of the coding protocol.

4.4.3. Development of the study coding protocol and reliability of coding

Similar to a survey questionnaire, study coding protocols are tailored to meet the specific requirements of individual meta-analyses that may vary considerably in scope and objectives. Therefore, a one-size fits all approach is not applicable for developing coding protocols and, “there is no such thing as the perfect illustrative coding scheme” (Hunter & Schmidt, 2004: 471). However, generic guidelines have been formulated by meta-analysis experts to assist in the development of study coding protocols (Hunter & Schmidt, 2004). Therefore, the coding protocol for the current meta-analysis (see Appendix-2) has been framed in accordance with the aims of the current study and by adhering to the general guidelines contained in the literature (e.g., see Cooper, 2010; Duriau, Reger & Pfarrer, 2007; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001). In addition to the guidelines and practice, the coding protocol was designed after examining a broad range of primary studies for data that renders itself to systematic coding.

The coding protocol for the present study conforms to the convention of dividing the protocol into separate sections depending upon the nature of the information being coded from incorporated studies. The first section describes study characteristics such as citation information, study context and sampling procedure. Space was also allocated for recording of miscellaneous information such as page numbers of the study from which information was extracted. Lipsey and Wilson (2001) assert that it is prudent to include such information to facilitate verification at a later stage (if required). The second section of the coding protocol concerned the empirical data and findings of studies such as effect sizes, moderator variables, reliability estimates and sample sizes. The reliability estimates enable corrections to the reported effect sizes for measurement errors.

For study coding, a further important matter concerned what is referred to as inter-coder reliability. The term is self-explanatory and refers to the degree of homogeneity between the information coded by independent researchers (see Lipsey & Wilson, 2001). A close investigation of scholarly recommendations and meta-analytic reviews revealed that the decision to engage a single or multiple coders is largely dictated by the scope of the meta-analytic study, and the degree of objectivity/subjectivity of the data (see Hunter & Schmidt, 2004). Due to the fact that the current meta-analysis involves a bivariate relationship and data required to be coded is objective, no scope for disagreements was anticipated between multiple coders. Therefore, a single coder undertook the coding task in this study. The decision to engage a single coder is supported by meta-analytic experts. For example, Hunter and Schmidt (2004) suggest that for coding objective data (versus subjective data) from studies, there appears to be very little possibility of inter-coder disagreement, given the factual nature of the coding task. Similarly, Whetzel and McDaniel (1988) conclude that, for objective data, coding involving bivariate associations and few hypothesised moderation effects, the inter-coder agreement was found to be nearly perfect. They argue that meta-analyses characterised by objective coding are neither required to engage multiple coders nor report inter-coder reliability information (see Cooper, 1998; Hunter & Schmidt, 2004; Whetzel & McDaniel, 1988).

However, to verify the accuracy of the coded data, re-coding of a subsample of incorporated studies was undertaken without any reference to the original data, as recommended by Lipsey and Wilson (2001). The coder examined a subsample comprising 20 randomly selected studies (out of 57 incorporated) three months after coding was initially performed and completed. Results of the two coding tasks were compared to check for any discrepancies and the coded data was found to be perfectly accurate.

The coding of moderator variables was conducted, as outlined next, to enable the investigation of conditions under which PIC–firm performance relationship may change in magnitude and/or direction. Decisions guiding the coding of

potential moderators are explained alongside a brief description (where relevant) of external data sources.

4.4.4. Detection and coding of moderator variables

Enabling the investigation of moderator variables is amongst the salient advantages of meta-analyses, as moderators assist in the delineation of boundary conditions of a theory (Aguinis et al., 2011; Viswesvaran & Ones, 1995). Alternative methods are used to detect the presence of moderator variables and the two commonly employed methods are the Schmidt and Hunter's 75 percent rule and the Hedges and Olkin procedures. In the Schmidt and Hunter method, a 75 percent threshold is used for examining the variance in correlations, for detecting the presence of moderators (Hunter & Schmidt, 1990). Although in frequent use and driven by strong rationales, the applicability of this method in fields other than psychometrics, for which it was originally formulated, has been called into question (Borenstein et al., 2009). Therefore, this method was not adopted in the current study.

In the Hedges and Olkin method, the χ^2 (Chi-square) test of homogeneity is employed to evaluate if the variance of effect sizes can be solely attributed or not to sampling error (Borenstein et al., 2009). If the χ^2 value is statistically significant, examination of possible moderators becomes necessary (Kirca et al., 2005). The χ^2 test is frequently used in meta-analyses and was employed in the current study owing to its statistical rigour and scholarly acceptance outside the field of psychometrics. Considering the categorical nature of potential moderators in the study, subgroup analyses were used to ascertain the moderation effects on the PIC–firm performance relationship. The variables were coded only when unambiguous information was reported in studies, in order to avoid confounding moderation results. Studies not reporting explicit information on moderators were coded 'NA' (Not Available), in the corresponding column of the coding sheet.

Borenstein et al. (2009) recommend that at least 10 studies must be used for the analysis of each purported moderator variable, and the current study

meets this heuristic. Measures enabling the coding of moderator variables and evaluation of their effects were adopted on the basis of: the convention followed in meta-analyses; the scope of the current study and, the operationalisation of PIC as a dynamic capability (e.g., see Grinstein, 2008a; 2008b; Kirca et al., 2011; Rosenbusch et al., 2011; Rubera & Kirca, 2012). The coding of moderators is now outlined.

4.4.4.1. Industry type

The type of industry was divided into two broad categories (i.e., manufacturing and service) to enable the testing of any moderation effect via subgroup analysis. Information on industry type was extracted from studies to group effect sizes by industry type. Grouping was simply based on whether a study investigated a sample of manufacturing or service firms and the two groups were subsequently subjected to analysis to determine if statistically significant differences existed between them. Manufacturing and service firm samples were coded as “manufac” and “service” respectively. Such coding for categorical variables is prescribed by meta-analysts (e.g., Aguinis & Pierce, 1998). Thirty one studies provided information on industry type (i.e., manufacturing or services), thereby enabling a sub-group analysis.

4.4.4.2. Firm size

Based on contentions concerning the potential impact of firm size on the relationship of interest (presented in Chapters-2 and 3), effect sizes were grouped in accordance with SMEs and large firms to examine differences between the two groups. To differentiate SMEs from large corporations, different benchmarks have been used in the literature, and there is no universally applied rule of thumb for such categorisation (Rosenbusch et al., 2011). As the largest number of studies incorporated in the present research originated from the US (i.e., 20 studies out of 57), the SME definition applied in this study corresponded with the US threshold for SME classification. The US threshold stipulates 500 full-time employees as the demarcation between SMEs and large firms. This dichotomy is also consistent with the threshold level used in many primary and meta-analytic studies (e.g., Acs & Audretsch,

1987; Rosenbusch et al., 2011). Consequently, the correlations from studies investigating firms with less than or equal to 500 employees were grouped in the SME cluster. A total of 27 studies supplied data on the size (SMEs or large firms) of the sampled firms.

4.4.4.3. Technological turbulence

The metrics used for dichotomising technological turbulence as high or low in this study were: the country-level R&D expenditure as the percentage of Gross Domestic Product (GDP), the number of researchers in R&D per million people, and the number of patent applications by local residents per million people.

These measures are reflective of the characteristics of technological turbulence (as outlined in Chapters-2 and 3), and identical or similar measures are frequently adopted in meta-analyses and primary studies (e.g., Grinstein, 2008b; Nelson, 1993; Song et al., 2005; Thornhill, 2006; Wilhelm et al., 2015). The use of R&D expenditure as a percentage of GDP for operationalising technological turbulence at country-level (in this study) was predicated on, and analogous to, the use of R&D intensity as a measure of industry- and firm-level R&D efforts (e.g., see Neely & Hii, 1998; Scherer, 1965; Thornhill, 2006). The number of researchers in R&D per million people is an established measure for calibrating knowledge assets/intellectual capital (see DeCarolis & Deeds, 1999; Thornhill, 2006). The number of patent applications by local residents per million people served as a measure of technological outputs, the key contributor to turbulence. The three measures calibrated resource commitments towards, and also outcomes relating to, technological advances. Hence, it is argued that the measures collectively constituted a valid and comprehensive metric for assessing technological turbulence prevailing in a specific country, and for evaluating its moderation effects. Other meta-analyses have examined the moderation effects of technological turbulence with similar measures (e.g., see Grinstein, 2008b).

In addition to the appropriateness of these measures for operationalising technological turbulence, they also overlap with the frequently used measures

for market dynamism. Through the inclusion of R&D expenditure as a percentage of GDP in the metric, technological turbulence was operationalised in a manner similar to the firm/industry-level operationalisation of market dynamism via R&D intensity (e.g., see Audretsch & Acs, 1991; Thornhill, 2006; Zhang et al., 2013). Furthermore, employing the number of researchers in R&D per million people corresponds to the measure of knowledge assets/skilled human capital, as sometimes used to calibrate market dynamism (e.g., Thornhill, 2006). Thus, due to the significant overlap between the measures of technological turbulence and market dynamism, the suitability of employing technological turbulence as a proxy for market dynamism in the current study is further supported.

The data for coding technological turbulence as high or low was obtained from the online Science and Technology Databases of The World Bank. These databases provided information on several country-specific indicators of science and technological activities such as high technology exports, scientific and technical publications, and R&D expenditure (as a percentage of GDP), amongst others (see <http://data.worldbank.org/topic/science-and-technology>, for details). The composite country scores (obtained by combining country-specific scores for each of the three measures) were used to determine the level of technological turbulence prevailing in a market. In total, 45 studies were coded for technological turbulence to enable a sub-group analysis. The moderator was coded as high or low, depending upon whether the composite score of a country fell above or below the median score, respectively.

4.5. CORRECTING THE EFFECT SIZES FOR ARTIFACTS

Artifacts generally produce attenuation in study results, which means that artifacts cause effect size values to become smaller in value (Borenstein et al., 2009). Therefore, the artifact correction framework prescribed by Hunter and Schmidt (1990) was employed for corrections to estimate the disattenuated (i.e., artifacts-corrected) correlations. The disattenuated correlations were greater in magnitude than the reported (attenuated) correlations, as is

characteristically the case in all meta-analyses. The elimination of artifacts enabled the computation of a summary estimate of the PIC–firm performance relationship that is largely free from sampling and reliability (of measurement) errors (see Aguinis & Pierce, 1998).

Additionally, a more accurate assessment of the moderation effects is possible after the corrections, because a large proportion of the observed variance in the effect size dataset potentially stems from the presence of artifacts (Hunter & Schmidt, 1990; 2004). Thus, corrections were made to eliminate the sources of spurious variation before attempting to estimate moderation effects as prescribed by Hunter and Schmidt (1990; 2004). As meta-analyses generally account for sampling and measurement errors (e.g., see Grinstein, 2008a; 2008b; Kirca et al., 2011; Leuschner et al., 2013; Rubera & Kirca, 2012; Sivasubramaniam et al., 2012), these two artifacts are now discussed in the context of the current study.

4.5.1. Correction for sampling error

Sampling error is present in all primary studies and it indicates the extent to which the firm samples studied do not accurately represent the populations from which they are drawn (Särndal, Swensson & Wretman, 1992). Sampling error causes deviations in study findings from what would be the case if no sampling error was present, and its influence on correlations is essentially unsystematic (Hunter & Schmidt, 1990). Due to the unsystematic effect of the sampling error, no corrections are possible in individual correlations (Hunter & Schmidt, 2004).

Thus, no specific corrective computations could be performed in this study to eliminate or minimise sampling error. The magnitude of the unsystematic effect of sampling error is chiefly determined by the size of the overall firm sample in a meta-analysis (Hunter & Schmidt, 2004). Consequently, it is expected that the present study is not entirely free of sampling error. However, due to an appreciable cumulative sample size (N) of 13,911 firms, sampling error is not expected to distort the meta-analytic results considerably. The value of N (i.e., 13,911 firms) in this study is in the vicinity of the cumulative

sample sizes in many other meta-analyses (e.g., see Büschgens et al., 2013; Read et al., 2009).

By contrast, the correction for measurement error can be undertaken on individual effect sizes if reliability estimates are reported in incorporated studies. Most meta-analyses employ corrections for measurement error and such corrections were undertaken in the current study, as outlined next.

4.5.2. Correction for measurement error

The correction for measurement error was undertaken by adopting the guidelines prescribed by Hunter and Schmidt (1990). This error was corrected by factoring in reliability estimates reported in studies. Reliability estimates are squares of corresponding factor loadings (Grawe et al., 2009). Unfortunately, several incorporated studies did not report the reliability estimates for their measures. This problem is commonly encountered and the general practice is to either compute a simple average (e.g., see Kirca et al., 2005; Geyskens et al., 1998; Stam et al., 2014), or sample size-weighted average of the reported reliability estimates (e.g., see Kellermanns et al., 2011; Sivasubramanian et al., 2012). Either of the two averages is assigned to the studies not reporting this data.

While both approaches have scholarly acceptance as outlined above, the latter (weighted average) was used in this study. The premise underlying the preference for a weighted average was that studies with large samples are likely to report more accurate reliability estimates. Thus, a weighted average factors in the relative precision of individual studies, as indicated by their respective sample sizes. The values were computed using a generic formula for weighted averages as shown below (and contextualised for the current study):

Weighted average of reported reliability estimates=

$$\frac{\sum(\text{Sample size of study reporting reliability} \times \text{corresponding reliability estimate})}{\sum(\text{Sample sizes of studies reporting reliability estimates})} \quad \text{-Formula-4.3}$$

Where, X and \sum represent multiplication and summation respectively.

Incorporated studies with unreported reliability estimates were assigned reliability values of 0.834 for PIC and 0.908 for firm performance (e.g., Penner-Hahn & Shaver, 2005; Thornhill, 2006; Lööf & Heshmati, 2006). The rationale for assigning the average of reliability estimates to missing (unreported) values was that the overall correction is superior with, rather than without, the assignment of average reliabilities to studies missing this information.

All effect sizes were individually disattenuated by dividing them by the product of the square root of the IV and DV reliabilities (see Hunter & Schmidt, 1990; 2004; Schmidt & Hunter, 1996). Hence, in accordance with scholarly recommendations, the formula used for disattenuation of PIC–firm performance effect sizes was:

$$r_{\text{corrected}} = r_{\text{reported}} / (R_{\text{PIC}} \times R_{\text{Firm performance}})^{1/2} \quad \text{-Formula-4.4}$$

where, ' R_{PIC} ' and ' $R_{\text{Firm performance}}$ ' denote reliabilities for the IV and DV respectively; ' r_{reported} ' is the attenuated correlation reported in the study and ' $r_{\text{corrected}}$ ' is the disattenuated correlation corrected for measurement errors. Exponent ' $1/2$ ' denotes the square root of the denominator and ' \times ' denotes multiplication.

(Hunter & Schmidt, 2004)

The formula-4.4 is essentially identical to Formula-4.1 (presented in Section-4.3), but used here to make corrections for measurement errors (it was earlier used for adjusting correlations in compliance with the weighting scheme). Incorporated studies using archival data, such as Artz et al. (2010) and Schoenecker and Swanson (2002), were accorded reliabilities of one, as the data used for analysis in such studies was objective and not subjective (e.g., see Read et al., 2009). The effect sizes were synthesised subsequent to undertaking the adjustments based on the weighting scheme, and corrections for measurement errors. The procedure used for obtaining the summary effect size is now outlined.

4.6. SUMMARY EFFECT SIZE COMPUTATION

4.6.1. Averaging correlations within studies

Several incorporated studies reported multiple correlations for the relationship under investigation (e.g., Akgün et al., 2009; Chen et al., 2009; Coombs & Bierly, 2006). The correlations from such studies were combined into a single effect size before they were synthesised. Reporting of multiple correlations in a single study was generally a result of deploying diverse measures for either PIC or firm performance, or both. For example, Vorhies and Morgan (2005) reported separate correlations for two firm performance measures, namely, profitability and return on assets. Similarly, Ar and Baki (2011) reported separate correlations for product and process innovation that together constitute PIC (see O'Cass & Ngo, 2012 for PIC definition). In such cases, the following arguments underpinned the averaging of multiple correlations reported in a single study.

It is a common practice in meta-analyses to synthesise effect sizes based on different IV or DV measures (e.g., Kirca et al., 2005; Kirca et al., 2011; Rosenbusch et al., 2011). This practice supports the argument for averaging multiple correlations that are based on different but conceptually similar measures that are reported in a single study. Lipsey and Wilson (2001: 101) highlight this convention and its appropriateness by asserting that “the usual ways of handling multiple effect sizes [...] are to either select a single effect size from amongst them or average them into a single mean value”. Therefore, multiple effect sizes for the PIC–firm performance relationship reported in the incorporated studies were averaged to obtain a single effect size value, as in Ar and Baki (2011), Wolff and Pett (2006) and Yam et al. (2011). This also ensured that every study reporting multiple effect sizes was included only once to preclude their overrepresentation in the summary effect size. The imperative of preventing overrepresentation has been underscored in several meta-analyses (e.g., Read et al., 2009; Rosenbusch et al., 2011; Sivasubramaniam et al., 2012). It has also been clearly articulated by Rosenbusch et al. (2011: 448), who state that:

Where articles based on the same sample reported different effect sizes because they linked different innovation measures to different performance measures, we calculated average effect sizes and included each sample only once based on average effect sizes.

Conversely, separate publications investigating the same constructs and firm sample, but reporting multiple effect sizes for the relationship of interest, were included only once in the summary effect size computation, as in Li and Atuahene-Gima (2001; 2002). Inclusion of such studies only once was achieved through averaging the reported correlations. Consequently, the possibility of any firm sample being overrepresented through multiple inclusions in the dataset was eliminated. This averaging of multiple correlations reduced the dataset from the original 81, to 58 correlations. The 58 correlations were subsequently aggregated, as discussed in the next Section.

4.6.2. Aggregating correlations across studies

As the summary effect size is analogous to a weighted average, which is commonly used in descriptive statistics, and represents the systematic aggregation of the disattenuated effect sizes (i.e., the correlations that have been corrected for artifacts) (Borenstein et al., 2009). Fisher's z-transformation and Hunter and Schmidt are the most commonly used approaches for obtaining the summary effect size (see Borenstein et al., 2009). The Hunter and Schmidt approach advocates that summary effect size calculations should be directly performed on correlations. On the other hand, Fisher's z-transformation involves converting correlations into z-coefficients (Hedges & Olkin, 1985; Kirca et al., 2005). Importantly, the standard-error of a z-coefficient is exclusively contingent upon the sample size and is unaffected by the magnitude of the z-coefficient itself, making the z-transformation a potentially superior method (see Geyskens et al., 2009). Several meta-analyses have employed Fisher's z-transformation method (e.g., see Grinstein, 2008b; Kirca et al., 2005; Kirca et al., 2011; Rubera & Kirca, 2012). Hence, Fisher's z-transformation was preferred over the Hunter and Schmidt

approach for obtaining the summary effect size in the current study. The formula used for computing z-coefficients is:

$$\text{z-coefficient} = 0.5 * \ln \left\{ \frac{(1 + \text{Correlation})}{(1 - \text{Correlation})} \right\}; \text{ with the standard error of z-coefficient} = 1/(N-3)^{1/2}, N = \text{sample size of the study, } \ln = \text{natural log, and '–' (en dash) denotes subtraction. Exponent '1/2' and * (Asterisk) represent square root and multiplication respectively. (Borenstein et al., 2009)}$$

The z-coefficients were then weighted by an estimate of the inverse of their variance and subsequently averaged (see Hedges & Olkin, 1985). This weighting ensured that studies with large samples were conferred proportionately greater importance. Finally, the weighted average of the z-coefficients was transformed back into the original correlation metric for reporting as the summary effect size (see Hedges & Olkin, 1985). This step was performed via a suitable software program (discussed later in the Chapter).

Some studies reported effect sizes that fell outside the usual range (approximately, from 0.00 to 0.60) of effect sizes extracted. For example, Penner-Hahn and Shaver (2005) reported a correlation coefficient of '–0.11', and this study could be considered an outlier by many researchers. Outliers are “studies whose effects differ very substantially from the others” (Borenstein et al., 2009: 368). While outlier values such as the correlation reported by Penner-Hahn and Shaver (2005) are generally substantive, they can also be consequent upon the presence of transcriptional and computational errors (Gulliksen, 1986). Hence, the method adopted for a sensitivity analysis of outliers is discussed next, in addition to other types of sensitivity analyses that were undertaken in the current meta-analysis.

4.7. OUTLIERS AND SENSITIVITY ANALYSES

Outlier identification and appraisal of their impact on findings is a challenging and complex matter (Hunter & Schmidt, 2004), and an outlier sensitivity analysis is strongly recommended to estimate the extent to which outliers

affect findings (e.g., Borenstein et al., 2009; Geyskens et al., 2009). Despite the importance accorded to it by researchers, a large majority of meta-analyses conducted in management do not report outlier sensitivity analyses (Geyskens et al., 2009).

Outlier sensitivity analyses in the present study were conducted in adherence to the guidelines offered by meta-analysts (e.g., Borenstein et al., 2009; Geyskens et al., 2009; Huber, 1980; Lipsey & Wilson, 2001; Tukey, 1960). The analyses entailed a direct comparison of results obtained with the entire dataset and those obtained with the dataset without outliers. Following the recommendations of Tukey (1960) and Huber (1980), top and bottom five percent of correlations (in terms of magnitude) were dropped from the dataset and a meta-analysis was performed on the remaining correlations. Thus, 10 percent of the correlations were identified as outliers in the current dataset. Hence, the summary effect size obtained with the removal of six correlations (i.e., 10 percent of the dataset values) comprising three correlations (i.e., five percent) each from the top and bottom ends, was compared with the summary effect size generated by the entire dataset.

Other types of sensitivity analyses also involved a comparison of the summary effect sizes obtained with the methods actually adopted, and the summary effect sizes from alternative meta-analytic decisions. The sensitivity analyses undertaken in this study (in addition to the outlier analysis) were:

1. Comparison of the summary effect sizes yielded with deployment of RE and FE models;
2. Comparison of the summary effect sizes obtained with and without making corrections for measurement errors, and
3. Comparison of summary effect sizes with and without the assignment of adjustment factors to individual correlations.

These types of sensitivity analyses are considered by meta-analysis experts as desirable (e.g., Borenstein et al., 2009; Cooper, 2010); however, the sensitivity analysis listed third in the list is unique to the current study and

unprecedented. The results of all sensitivity analyses are reported in the next Chapter.

It should be noted that a sensitivity analysis concerning sample size outliers (i.e., studies with extremely large sample sizes) was excluded in the current study as advised by Geyskens et al. (2009). This is because the studies with large firm samples are expected to provide a superior estimate of the true (construct-level) effect size, and their removal from the data-analysis can generally not be justified (Geyskens et al., 2009).

In addition to the sensitivity analyses, meta-analysts strongly recommend an estimation of publication bias that may distort meta-analytic results and thereby detract from their reliability (e.g., Aguinis et al., 2011; Geyskens et al., 2009; McDaniel, Rothstein & Whetzel, 2006; Rosenthal, 1995). The methods adopted for its estimation in the current study are outlined next.

4.8. THE ASSESSMENT OF PUBLICATION BIAS

To enhance the reliability of meta-analytic results, it is vital to detect the presence of, and estimate, publication bias (Aguinis et al., 2011; Hunter & Schmidt, 1990; Rosenthal, 1979; 1995). However, only a small proportion of meta-analyses undertaken in management have estimated publication bias (Geyskens et al., 2009). Publication bias occurs due to the general propensity of peer-review process to favour studies reporting statistically significant results for publication, rather than studies reporting non-significant results (Cooper, 2010). This potentially creates a biased representation of prior research in a meta-analysis. In other words, published studies are unlikely to accurately represent the entire population of studies (i.e., both published and unpublished) conducted in the past (Hunter & Schmidt, 1990; Rosenthal, 1979; 1995), and indeed, are likely to over-estimate the true effect size.

There are several approaches to detecting and quantifying publication bias such as the Rosenthal's file drawer analysis (see Rosenthal, 1979; 1995),

Orwin's fail-safe N (see Orwin, 1983), Begg and Mazumdar's rank correlation (see Begg & Mazumdar, 1994), Egger's regression intercept (see Egger, Smith, Schneider & Minder, 1997), and the Duval and Tweedie's trim-and-fill method (see Duval & Tweedie, 2000a; 2000b; McDaniel et al., 2006). However, the two most commonly employed approaches are the Trim-and-fill method and Rosenthal's file drawer analysis.

Rosenthal's file drawer analysis enables the computation of the number of unpublished studies reporting null (i.e., statistically non-significant) results (Hunter & Schmidt, 2004; Rosenthal, 1979; 1995). The number of such unpublished studies is referred to as the Rosenthal's *fail-safe N* (Rosenthal, 1979). Despite the acceptance of *fail-safe N* in the literature, the Duval and Tweedie's Trim-and-fill method is often regarded as a superior method by many researchers (e.g., Aguinis et al., 2011; Borenstein et al., 2009; Cooper, 2010; Geyskens et al., 2009), as it has the following advantages:

- 1) The Trim-and-fill method enables the calculation of a missing studies-adjusted summary effect size, and determination of the magnitude of difference between the observed and adjusted summary effect sizes (Aguinis et al., 2011). Thus, the method addresses a significant question, "*what is our best estimate of the unbiased effect size [emphasis in original]?*" (Borenstein et al., 2009: 286), and
- 2) Through a funnel plot (a salient feature of this method), the researcher can visually assess (albeit somewhat subjectively) the extent of publication bias in a dataset (Borenstein et al., 2009).

While Duval and Tweedie's Trim-and-fill method potentially possesses advantages over the Rosenthal's file drawer analysis, the latter is very popular and historically important (Borenstein et al., 2009). Thus, both the approaches were adopted, also because they provided insights about the file drawer problem from somewhat different perspectives, and with different statistics, namely, the *fail-safe N* and the missing studies-adjusted summary effect size.

The analysis and results of the file drawer problem (using the two methods outlined here) are presented in the next Chapter.

To assess the file drawer problem and perform computations as discussed in this Chapter (with the exception of the weighting scheme), a software program was procured. The selection of an appropriate software program for the current meta-analysis is now discussed, and this was the final decision concerning the study design and methodology.

4.9. META-ANALYSIS SOFTWARE

Meta-analytic calculations such as the summary effect size calculation, artifactual corrections, and the detection of moderation effects are facilitated by employing computer software. Although spreadsheet programs (e.g., MS Excel) and statistical packages (e.g., SPSS, SAS, AMOS and LISREL) are occasionally used for some meta-analytic procedures, they are not specifically designed for meta-analyses. Spreadsheets have limitations as they lack important meta-analytic tools, such as forest plots, and the generic statistical packages do not aid in the assignment of sample size-derived weights to individual effect sizes (Borenstein et al., 2009). Consequently, the deployment of specialised software, in this case, Comprehensive Meta-Analysis (CMA), was considered as several meta-analyses have employed CMA (e.g., Brinckmann et al., 2010; Chan, Ruest, Meade & Cook, 2007; Dalton, Daily, Certo & Roengpitya, 2003).

CMA integrates the guidelines of Hunter and Schmidt (1990; 2004), Hedges and Olkin (1985), and Lipsey and Wilson (2001), thus offering comprehensive features for conducting meta-analyses. Hence, CMA was procured and used for data-analysis, after a limited-period trial version of the software was tested and found to be compatible with the scope and aims of this study.

4.10. CHAPTER SUMMARY

The research design and methodology described in the Chapter were developed after an extensive review of meta-analytic practices, in conjunction with consideration of the specific aims of this study. The study inclusion criteria and coding protocol were devised by following the guidelines prescribed in the literature, and considering the specific data requirements for the PIC–firm performance meta-analysis. The coding of potential moderators was based on an examination of their conceptualisation and operationalisation.

Other important decisions, such as those concerning unreported data (e.g., unreported reliabilities and the average size of sampled firms) and computational procedures (e.g., adjustments made to correlations), were explicitly described in the Chapter. The study design and research methods adopted were predicated on scholarly prescriptions, conventions followed in the literature and the research aims of this study. The next Chapter presents the actual data-analysis and the results obtained, after subjecting the dataset to the procedures presented in this Chapter.

CHAPTER FIVE

DATA ANALYSIS AND FINDINGS

5.1. INTRODUCTION

This Chapter describes and presents the results of the data analysis performed on the dataset of studies that satisfied the criteria, as outlined in Chapter-4. The effect size weighting scheme and the meta-analytic procedures for obtaining a summary effect size and for detecting moderation effects (as discussed in Chapter-4), dictate the data-analysis presented in the Chapter. The data-analysis results presented were imported into MS Word for presentation from the software program Comprehensive Meta-Analysis (CMA) Version-2, used in the current study for meta-analytic computations. The nomenclature for data analysis and presentation of findings used in this Chapter complies with CMA program and the book *Introduction to Meta-analysis*, by Borenstein et al. (2009). Both the program and book share a common terminology and notation.

The Chapter commences with an overview of studies that were incorporated for the meta-analysis, and then the results of the analysis for obtaining a summary effect size are presented. Wherever applicable, confidence intervals (CIs), forest plots and heterogeneity analyses are presented in conjunction with data-analysis procedures and salient findings. The results of moderator analyses follow, and the Chapter concludes with outlier and sensitivity analyses, and an estimation of any publication bias.

5.2. STUDY CHARACTERISTICS

AND OVERVIEW OF CODED DATA

5.2.1. Extracted effect sizes (correlation coefficients)

The effect sizes reported in incorporated studies varied from a high of 0.82 by Mithas, Ramasubbu and Sambamurthy (2011) to a low of '−0.3' reported by Richard et al. (2003). Positive effect sizes were reported by 52 studies while five studies reported a negative correlation for the PIC–firm performance relationship. In total, 81 correlation coefficients representing the relationship between the IV (PIC) and DV (firm performance) were synthesised from 57 studies (comprising 58 independent samples) in the meta-analysis. The effect sizes were subjected to adjustments based on the weighting scheme (outlined in Chapters-3 and 4) and meta-analytic calculations through the use of CMA.

5.2.2. Reported and unreported reliability estimates

A total of 49 studies reported reliability estimates for at least one variable (either PIC or firm performance); the remaining eight studies did not report reliabilities for any variable. The reliabilities for these eight studies and other studies, having missing reliability values (for either of the two variables), were assigned in accordance with the practice of using the weighted mean value of the reported reliabilities, as explained in Section-4.4. The weighted averages obtained for reliabilities using Formula-4.3, for PIC and firm performance, were 0.834 and 0.908, respectively. These values were assigned to the studies with missing reliabilities.

The reliabilities of PIC ranged from a Cronbach Alpha of 0.65 to 0.98, as reported by Garg et al. (2003) and Lee et al. (2001), respectively. For firm performance, the reliabilities ranged from 0.72 to 0.95, as reported by O'Cass and Sok (2013b) and Lee et al. (2001), respectively. These reliability values pertain to subjective, itemised measurement scales; the value given to the measures exclusively employing objective data was 1.00 (e.g., see Kalafsky &

MacPherson, 2002; Katila & Ahuja, 2002). All the individual, study-specific reliability estimates are provided in Table 5.1. Sizeable variation in other variables (e.g., effect sizes, sample sizes) across incorporated studies can also be observed in the Table, and further description of the coded data is provided next.

5.2.3. Characteristics of firm samples

The incorporated studies vary considerably in their sample characteristics. The largest and smallest study samples comprised 1,413 firms reported by Heeley et al. (2007) and 46 firms reported by Kuckertz et al. (2010), respectively. In adherence with meta-analytic procedures, the disparate sample sizes were factored in by CMA software for computing summary effect size, so that studies with large samples are assigned proportionately greater importance. The cumulative sample size (N) of firms for the current meta-analysis is 13,911.

The names (Authors, Year) of the coded studies and relevant information for summary effect size calculations are also presented in the Table 5.1. Microsoft (MS) Excel was used for creating the database as it is generally preferred for data tabulation. Furthermore, data created in Excel renders itself to easy export into MS Word and CMA, for presentation and meta-analysis, respectively. Unreported reliability estimates are represented as NA (Not Available), and the weighted averages (for PIC and firm performance) of reliability estimates are substituted for such missing values (as stated in the previous Section). A reliability estimate value of 1.00 signifies archival or objective data.

Table 5.1: Basic study coding data

Study [Author(s), Year]	Journal name	Sample size	Reported effect size (correlation coefficient)	Reliability estimates (1st value IV, 2 nd DV)
Akgün et al. (2009)	<i>Journal of Engineering and Technology Mgmt</i>	163	0.555 ([#] Av of 0.54, 0.57)	0.81 (Av of 0.84, 0.78), 0.91
Ar and Baki (2011)	<i>European Journal of Innovation Mgmt</i>	270	0.19 (Av of 0.23, 0.15)	0.90 (Av of 0.88, 0.92), *NA
Aragon-Correa et al. (2007)	<i>Industrial Marketing Management</i>	408	0.509	0.777, 0.889
Artz et al. (2010)	<i>Journal of Product Innovation Mgmt</i>	272	0.05 (Av of 0.01, 0.09)	1, 1 (Archival data)
Baer and Frese (2003)	<i>Journal of Organisational Behaviour</i>	47	0.13	0.74, 1
Calantone et al. (2002)	<i>Industrial Marketing Management</i>	187	0.4	0.89, 0.85
Chen, Lin & Chang (2009)	<i>Industrial Marketing Management</i>	106	0.463	0.828, 0.814
Chen, Tsou & Huang (2009)	<i>Journal of Service Research</i>	123	0.59 (Av of 0.57, 0.61)	0.947, 0.939 (Av of 0.946, 0.932)
Coombs and Bierly (2006)	<i>R&D Management</i>	201	0.13 (Av of 0.29,- 0.29,0.64,0.04,0.13,-.02)	1, 1 (Archival data)
Craig and Dibrell (2006)	<i>Family Business Review</i>	360	0.22	0.78, 0.89
Cui et al. (2005)	<i>Journal of International Marketing</i>	131	0.582	0.86, NA
Dai and Liu (2009)	<i>International Business Review</i>	711	0.23	0.72 (Av of 0.73, 0.71), 0.85
Deeds et al. (1998)	<i>Entrepreneurship: Theory and Practice</i>	89	0.23	NA, NA
Dibrell et al. (2008)	<i>Journal of Small Business Management</i>	397	0.195 (Av of 0.20, 0.19)	0.735 (Av of 0.78, 0.69), 0.88
Eisingerich et al. (2009)	<i>Journal of Service Research</i>	114	0.68	NA, 1
Ettlie and Pavlou (2006)	<i>Decision Sciences</i>	45	0.32	0.85, NA
Garcia-Morales et al. (2007)	<i>Technology Analysis and Strategic Management</i>	246	0.483	0.802, 0.832
Garg et al. (2003)	<i>Strategic Management Journal</i>	105	0.01	0.65, NA
Gopalakrishnan (2000)	<i>Journal of High Technology Mgmt Research</i>	101	0.21	0.84, NA
Grawe et al. (2009)	<i>Int J of Physical Distribution & Logistics Mgmt</i>	304	0.41	0.89, 0.89
Guan and Ma (2003)	<i>Technovation</i>	213	0.14	0.94, 1
Heeley et al. (2007)	<i>Academy of Management Journal</i>	1413	0.07	NA, NA
Heunks (1998)	<i>Small Business Economics</i>	200	0.15 (Av of 0.1, 0.19 and 0.15)	NA, NA
Hult et al. (2004)	<i>Industrial Marketing Management</i>	181	0.47	0.88, 0.84
Jansen et al. (2006)	<i>Management Science</i>	283	0.18	0.86, 1
Jimenez and Valle (2011)	<i>Journal of Business Research</i>	451	0.41 (Av of 0.38, 0.44)	0.83 (Av of 0.81, 0.85), 0.83

<i>Study [Author(s), Year]</i>	<i>Journal name</i>	<i>Sample size</i>	<i>Reported effect size (correlation coefficient)</i>	<i>Reliability estimates (1st value IV, 2nd DV)</i>
Kalafsky and MacPherson (2002)	<i>Small Business Economics</i>	104	0.385	1, 1 (Archival data)
Katila and Ahuja (2002)	<i>Academy of Mgmt Journal</i>	124	-0.01	1, 1 (Archival data)
Kim et al. (2011)	<i>Journal of Business Research</i>	154	0.195	0.85, 1
Kuckertz et al. (2010)	<i>Int J of Technology Mgmt</i>	46	0.23 (Av of 0.3, 0.16)	0.75 (Av of 0.776, 0.721), 0.914
Lawson et al. (2012)	<i>R&D Management</i>	238	0.36	0.83, 0.71
Lee et al. (2001)	<i>Strategic Mgmt Journal</i>	137	0.45	0.98, 0.95
Li and Atuahene-Gima (2001)	<i>Academy of Mgmt Journal</i>	184	0.47, 0.455 (Av of 0.44, 0.47)	0.83 (Av of 0.88, 0.78), 0.88
Lin and Chen (2008)	<i>Int J of Organisational Analysis</i>	245	0.47	0.9, 0.86
Löf and Heshmati (2006) Sample-A	<i>Economics of Innovation and New Technology</i>	314	0.35	NA, NA
Löf and Heshmati (2006) Sample-B	<i>Economics of Innovation and New Technology</i>	838	0.17	NA, NA
Luo et al. (2005)	<i>Journal of the Academy of Marketing Science</i>	233	0.19	0.78, 1
Mithas et al. (2011)	<i>MIS Quarterly</i>	160	0.82	0.93, NA
O'Cass and Sok (2013a)	<i>Journal of Business Research</i>	157	0.49	0.88, 0.72
O'Cass and Sok (2013b)	<i>Int Small Business Journal</i>	171	0.65	0.89, 0.93
Panayides (2006)	<i>European Journal of Innovation Mgmt</i>	251	0.39	0.87, 0.93
Penner-Hahn and Shaver (2005)	<i>Strategic Mgmt Journal</i>	65	-0.11	NA, NA
Rhodes et al. (2008)	<i>Journal of Knowledge Management</i>	223	0.58	0.93, 0.88
Richard et al. (2003)	<i>Group and Organisation Mgmt</i>	177	-0.3	0.69, 1
Richard et al. (2004)	<i>Academy of Mgmt Journal</i>	153	0.18	0.80, NA
Salomo et al. (2008)	<i>Journal of Product Innovation Mgmt</i>	122	0.38	NA, 1
Schilke (2014)	<i>Strategic Mgmt Journal</i>	279	0.30	0.81, 0.93
Schoenecker and Swanson (2002)	<i>IEEE Transaction on Eng Management</i>	89	-0.074 (Av of -0.004, -0.108, -0.111)	1, 1 (Archival Data)
Sirén et al. (2012)	<i>Strategic Entrepreneurship Journal</i>	206	0.185 (Av of 0.25, 0.12)	0.71 (Av of 0.64, 0.79, 0.69, 0.71), 0.87
Tatikonda and Montoya-Weiss (2001)	<i>Management Science</i>	120	0.345 (Av of 0.42, 0.27)	NA, NA
Thornhill (2006)	<i>Journal of Business Venturing</i>	845	-0.02	NA, NA
Vorhies and Morgan (2005)	<i>Journal of Marketing</i>	230	0.28 (Av of 0.31 and 0.25)	0.8, NA
Wolff and Pett (2006)	<i>Journal of Small Business Management</i>	182	0.12 (Av of 0.14, 0.11)	0.645 (Av of 0.69, 0.60), 0.86

<i>Study [Author(s), Year]</i>	<i>Journal name</i>	<i>Sample size</i>	<i>Reported effect size (correlation coefficient)</i>	<i>Reliability estimates (1st value IV, 2nd DV)</i>
Yalcinkaya et al. (2007)	<i>Journal of International Marketing</i>	111	0.15	0.7, 0.87
Yam et al. (2004)	<i>Research Policy</i>	213	0.135 (Av of 0.151, 0.119)	(Av of 0.79, 0.91), 1
Yam et al. (2011)	<i>Research Policy</i>	200	0.324 (Av of 0.302 and 0.346)	0.82, NA
Zahra and Bogner (2000)	<i>Journal of Business Venturing</i>	116	0.18	0.71, NA
Zahra and Covin (1993)	<i>Strategic Mgmt Journal</i>	103	0.32	0.86, 1

[#]Av-Average
*NA-Not Available

Relevant columns of the data, namely, study names, effect sizes and sample sizes were exported from MS Excel to CMA software, as this information is necessary for computing a summary effect size. The Table 5.1 does not include the data coded for moderation analyses, which is presented in the next Section.

Before exporting data to CMA, correlations were subjected to adjustments in accordance with the effect size weighting scheme and disattenuation formula (presented in Chapter-4). The adjusted correlations aim to factor in the relative resource inputs for operationalising PIC more comprehensively. The adjusted correlations were subsequently subjected to corrections for measurement error via the procedures prescribed by Hunter and Schmidt (1990; 2004). Thereafter, the summary effect size was calculated and subgroup moderation analyses performed using CMA. The data collected on moderator variables is outlined next.

5.2.4. Data on moderator variables

Incorporated studies were examined for potential moderation effects as hypothesised in Chapter-3, and subjected to coding and computations in compliance with the methodology outlined in Chapter-4. Studies were coded for moderators on the basis of: 1. industry type (manufacturing or service), 2. firm size (large or SMEs) and 3. technological turbulence (high or low). Coding of technological turbulence was predicated on national-level scores

provided by The World Bank Science and Technology Databases (e.g., see Grinstein, 2008b).

Table 5.2 provides an overview of the data for the hypothesised moderator variables, obtained from studies included in the current meta-analysis. Most studies did not report information on all three moderators as their various research designs and aims did not require an examination of the variables used as potential moderators in the current meta-analysis. Manufacturing and services were coded as *manufac* and *service* respectively; similarly, SMEs were coded as *SME* and large firms as *large*. Technological turbulence was coded as *high* or *low* depending on whether country-specific composite scores were higher or lower than the median split of composite scores for the three measures of turbulence, as outlined in Section-4.4 (e.g., see Protogerou et al., 2012; Song et al., 2005).

Table 5.2: Summary of data on moderator variables

<i>Study</i>	<i>Industry type</i>	<i>Firm size</i>	<i>Technological Turbulence</i>
Akgün et al. (2009)	Mixed (both Manufacturing & Service)	Mixed (both Large firms and SMEs)	Low
Ar and Baki (2011)	*NA	SMEs	Low
Aragon-Correa et al. (2007)	Mixed	Large	High
Artz et al. (2010)	NA	Large	High
Baer and Frese (2003)	Mixed	NA	High
Calantone et al. (2002)	Mixed	Large	High
Chen, Lin and Chang (2009)	Manufacturing	Mixed	NA
Chen, Tsou and Huang(2009)	Service	NA	NA
Coombs and Bierly (2006)	Manufacturing	Large	High
Craig and Dibrell (2006)	Mixed	SMEs	High
Cui et al. (2005)	Mixed	Large	High
Dai and Liu (2009)	Mixed	SME	Low
Deeds et al. (1998)	Mixed	NA	NA
Dibrell et al. (2008)	Mixed	SME	High
Eisingerich et al. (2009)	Service	NA	NA

<i>Study</i>	<i>Industry type</i>	<i>Firm size</i>	<i>Technological Turbulence</i>
Ettlie and Pavlou (2006)	Manufacturing	Large	NA
Garcia-Morales et al. (2007)	Mixed	Large	High
Garg et al. (2003)	Manufacturing	SME	High
Gopalakrishnan (2000)	Service	Mixed	High
Grawe et al. (2009)	Service	NA	Low
Guan and Ma (2003)	Manufacturing	NA	Low
Heeley et al. (2007)	Manufacturing	Large	High
Heunks (1998)	Mixed	SMEs	NA
Hult et al. (2004)	Mixed	Large	High
Jansen et al. (2006)	Service	Large	NA
Jimenez and Valle (2011)	Mixed	Mixed	High
Kalafsky and MacPherson (2002)	Manufacturing	Mixed	High
Katila and Ahuja (2002)	Manufacturing	Mixed	NA
Kim et al. (2011)	Service	SMEs	Low
Kuckertz et al. (2010)	Mixed	SMEs	High
Lawson et al. (2012)	Mixed	Mixed	High
Lee et al. (2001)	Mixed	SMEs	High
Li and Atuahene-Gima (2001)	Mixed	SMEs	Low
Lin and Chen (2008)	Mixed	Large	NA
Lööf and Heshmati (2006), Sample-A	Service	Mixed	High
Lööf and Heshmati (2006), Sample-B	Manufacturing	Mixed	High
Luo et al. (2005)	Mixed	Mixed	Low
Mithas et al. (2011)	Mixed	Mixed	High
O'Cass and Sok (2013a)	Service	Mixed	NA
O'Cass and Sok (2013b)	Manufacturing	SMEs	NA
Panayides (2006)	Service	SMEs	High
Penner-Hahn and Shaver (2005)	Manufacturing	Mixed	High
Rhodes et al. (2008)	Mixed	Large	NA
Richard et al. (2003)	Service	Mixed	High
Richard et al. (2004)	Service	Mixed	High
Salomo et al. (2008)	Mixed	Large	NA
Schilke (2014)	Manufacturing	Mixed	High
Schoenecker and Swanson (2002)	Manufacturing	Mixed	High

<i>Study</i>	<i>Industry type</i>	<i>Firm size</i>	<i>Technological Turbulence</i>
Sirén et al. (2012)	Service	Mixed	High
Tatikonda and Montoya-Weiss (2001)	Manufacturing	Mixed	High
Thornhill (2006)	Manufacturing	SMEs	High
Vorhies and Morgan (2005)	Mixed	Mixed	High
Wolff and Pett (2006)	Mixed	SMEs	High
Yalcinkaya et al. (2007)	Manufacturing	Mixed	High
Yam et al. (2004)	Mixed	Mixed	Low
Yam et al. (2011)	Manufacturing	Mixed	High
Zahra and Bogner (2000)	Service	SMEs	High
Zahra and Covin (1993)	Manufacturing	NA	High

*NA-Not Available

The data collected for the analysis (presented in the Tables 5.1 and 5.2) was exported to CMA from MS Excel so as to undertake calculations and obtain meta-analytic results. The analysis of data is discussed next.

5.3. THE SUMMARY EFFECT SIZE AND HETEROGENEITY ANALYSIS


The analysis of data was undertaken in accordance with the methodology described in Chapter-4. The reported effect sizes were first adjusted using the procedures devised under the weighting scheme. These adjustments were performed manually, as due to the uniqueness of the weighting scheme, none of the available software packages enabled such computations. However, the summary effect size computations, and sub-group analyses for moderators, were performed using CMA. The data analysis and findings are presented next, commencing with the summary effect size and related findings. The subgroup analyses and findings for hypothesised moderation effects are presented subsequently.

5.3.1. Summary effect size and associated results

As outlined in Section-4.6, CMA does not compute the summary effect size directly from correlations but rather, transforms the correlations into their equivalent Fisher's z-coefficients. This procedure conforms to the commonly used Hedges and Olkin (1985) approach. Z-coefficients are averaged after they are weighted by an estimate of the inverse of their variance and reconverted back into a summary correlation, which is in the same metric as the reported correlations. The *Run Analyses* command on the data-entry interface of CMA was executed to obtain the summary effect size, Confidence Intervals and forest plots, as presented in Table 5.3. A Confidence Interval (CI) indicates the “precision with which the effect size has been estimated in that study” (Borenstein et al., 2009: 5), and 95% level is commonly used as an appropriate degree of precision. Therefore, a CI signifies the degree to which the summary effect size can be relied upon. The summary effect size results are for the RE model, which was deemed appropriate for the current study (see Section-4.2.1.).

The summary effect size for the relationship between PIC and firm performance was found to be 0.379 ($p < 0.05$). This constitutes a core finding of the current study. The summary effect size value of 0.379 represents the magnitude and direction of the relationship of interest. Judging by the heuristics proposed by Cohen (1977), the values of 0.10, 0.30 and 0.50 can be considered small, medium and large respectively; the summary effect size value obtained for the relationship can thus be considered moderately-large in magnitude. This suggests that PIC and firm performance are strongly related constructs. In Table 5.3, the columns labelled—Statistics for each study and, Correlation and 95 percent CI, present the numerical and visual forms of the summary correlation and CI. The labels—Favours A and Favours B, at the bottom of the forest plot are extraneous for the current study as they relate to experimental study designs that often use randomised controlled trials (e.g., see Chan et al., 2007). Also, as mentioned in the Table of Matrices, some compatibility issues between CMA and MS Word caused the Tables imported from CMA to not display optimally, but they are used for their scientific validity.

Table 5.3.: The summary effect size and CI

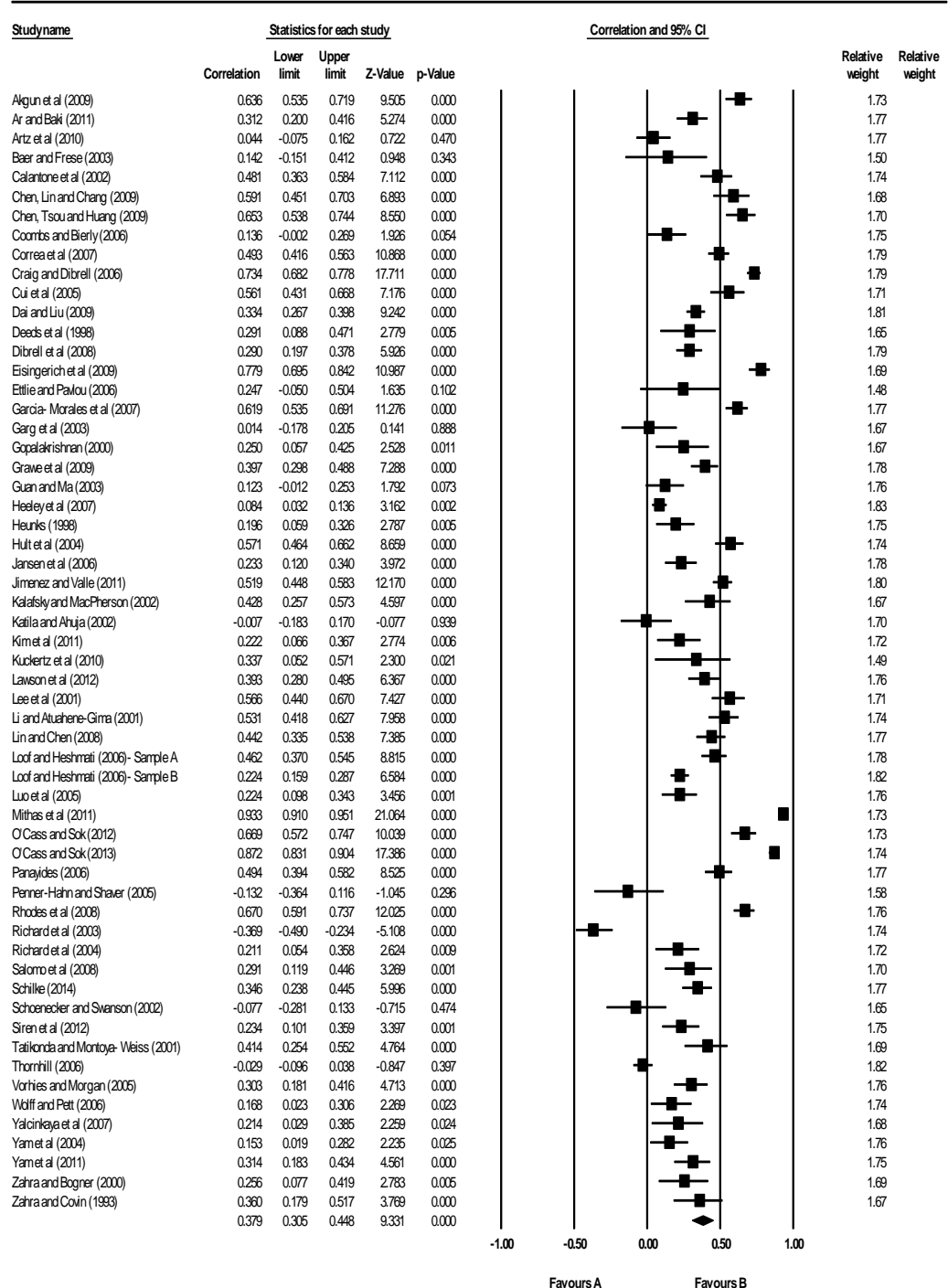
Summary effect-size and CI					
Study name	Statistics for each study				Correlation and 95% CI
	Correlation	Lower limit	Upper limit	Z-Value	p-Value
	0.379	0.305	0.448	9.331	0.000
					
Meta Analysis					

As can be seen in the Table, the $CI_{95\%}$ (i.e., the CI corresponding to a 95% confidence in the degree of precision) of the summary effect size ranged from a low of 0.305 to a high of 0.448. Hence, it can be concluded that the summary effect size of 0.379 is estimated with a high degree of precision. As the p -value is significant, and the CI does not encompass the value of zero (see Table 5.3), the possibility of a *Null* relationship between PIC and firm performance is dismissed and it is concluded that there is a significantly positive relationship between the two variables. Therefore, the first Hypothesis (H1) is supported.

The Table 5.4 presents the summary effect size and the corresponding CIs, both numerically and visually (via forest plots). Forest plots are extremely useful for visual interpretations and assessments of meta-analytic statistics, in addition to highlighting any problems with the dataset (Borenstein et al., 2009). “The forest plot is a compelling piece of information and easy to understand” (Borenstein et al., 2009: 366), and is therefore presented wherever applicable in this Chapter.

Table 5.4: Statistics for individual studies and forest plot

Summary High Resolution Plot



Meta Analysis

The mid-points and sizes (in terms of area) of the boxes in the forest plot represent individual correlations and relative weights (assigned to incorporated studies) respectively. The column labelled—Relative weight, on the extreme right of the Table 5.4., provides the weights assigned to the incorporated studies by CMA. The weights were largely determined by the relative sizes of the individual study samples (Borenstein et al., 2009), and calculated on the basis of the RE model in this study. The highest relative weight of 1.83 was accorded to Heeley et al. (2007), and lowest of 1.48 to Ettlie and Pavlou (2006), as the former has the greatest sample size of 1,413 firms and the latter has the smallest sample size of 45 firms. All other studies were also allotted weights in proportion to their relative sample sizes. This weight allocation conforms with the rationale of assigning higher weights to studies investigating larger firm samples (e.g., see Hedges & Olkin, 1985; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001). In essence, the weights reflect the relative influence of each individual study for obtaining the summary effect size value. It should be noted that the relative weights discussed here are completely extraneous to the firm size derived weights used for computing adjustment factors in the weighting scheme.

In Table 5.4, the distance of the boxes from the central line reflects the effect size magnitude on either side, with positive values being to the right and negative to the left of the central line. Five correlations are towards the left of the central vertical line (representing a correlation value of zero) in the forest plot, indicating negative reported (and also adjusted) effect sizes. A negative effect size indicates a negative relationship between PIC and firm performance, for those sampled firms in a study. It can, however, be observed in the correlations column that a majority (>50%) of adjusted effect size values are between 0.00 and 0.50, and the CIs vary from a low of 0.041 to a high of 0.563, for Mithas et al. (2011) and Baer and Frese (2003), respectively. The forest plot in the bottom row of Table 5.4 depicts the summary effect size and its $CI_{95\%}$ with a diamond-shaped quadrilateral. The width of the diamond represents $CI_{95\%}$ with the values of 0.305 and 0.448 lying at the extremes, and the centre of the diamond depicts the summary effect size value of 0.379.

5.3.2. Heterogeneity analysis

As H1 was supported by the summary effect size statistics, an analysis of the level of dispersion amongst adjusted correlations was then conducted. In addition to obtaining a summary effect size and testing for its statistical significance, assessing the dispersion of correlations is important so as to gain insights into the moderation effects of relationships under investigation (Aguinis & Pierce, 1998; Lipsey & Wilson, 2001; Viswesvaran & Ones, 1995). Appraising the heterogeneity of effect sizes in meta-analyses is analogous to an assessment of the variation in scores in a primary study. However, the heterogeneity metrics (discussed shortly) in meta-analyses are to be interpreted in relation to correlations and their distribution, rather than scores in a primary study.

The procedure for heterogeneity analysis used in this study was Hedges and Olkin (1984). As discussed in Chapter-4, this approach was chosen for its statistical rigour, over the 75 percent heuristic proposed by Hunter and Schmidt (1990). The Hedges and Olkin approach is centred on key statistics such as the homogeneity statistic (Q -statistic), degrees of freedom (df), Tau squared and I -squared (see Aguinis et al., 2011; Aguinis & Pierce, 1998; Borenstein et al., 2009; Hedges & Olkin, 1985; Hedges & Vevea, 1998). The results reported by CMA for the heterogeneity analyses are discussed next.

5.3.2.1. Testing for the presence of heterogeneity in true effect sizes

Heterogeneity assessment in meta-analyses entails estimating the variation that can be attributed to the dispersion amongst the true effect sizes in individual studies. As a starting point for heterogeneity assessment, the general practice is to propose a *Null* hypothesis that *all studies have a common effect size* (Aguinis et al., 2011; Borenstein et al., 2009). This hypothesis implies that all observed variance in reported correlations is a result of methodological errors (such as sampling errors), and it is required that this be tested so as to investigate heterogeneity in effect sizes and the presence of moderation effects.

The Q -statistic and the degrees of freedom (df) constitute the pivotal data that enable testing for the *Null* hypothesis. The relevant values are reported in Table 5.5. The Q -statistic represents the total observed variation of reported correlations and is computed by CMA by using the formula $Q = \sum W(Y - M)^2$ (Borenstein et al., 2009). In the formula, W , Y and M are study weights, effect sizes and the summary effect size, respectively. As evidenced by the formula, the Q -statistic is a weighted sum of squares of deviations of individual effect sizes from the summary effect size (see Borenstein et al., 2009). Degrees of freedom (df) is simply the number of independent samples minus one, and therefore takes the value of 57 ($58 - 1 = 57$) in the current study. Although the number of studies incorporated in the meta-analysis is 57, there are 58 independent samples being synthesised, as explained in Chapter-4. Therefore, the sample number is used in the formulae rather than the study number, in accordance with the fundamental rationales of data-analysis.

Table 5.5: Statistics for heterogeneity assessment

Effect size and 95% interval				Heterogeneity			
No of samples	Point estimate	Lower Limit	Upper Limit	Q-statistic	$df(Q)$	p -value	I -squared
58	0.379	0.305	0.448	1377.977	57	0.000	95.864

The Q -statistic for homogeneity complies with a central Chi-square (χ^2) distribution with degrees of freedom equal to $k-1$ (Aguinis et al., 2011, Borenstein et al., 2009; Hedges & Olkin, 1985). Thus, a p -value for the computed value of Q -statistic could be obtained. A p -value less than the level of significance leads to the *Null* hypothesis (i.e., all studies have a common effect size) to be rejected (see Borenstein et al., 2009). A screen-shot of the CMA-generated Table that reports the statistics presented in Table 5.5 is provided in Appendix-4.

Since the Q -statistic conforms to χ^2 distribution, a comparison between its p -value (for $Q = 1377.977$ and $df = 57$ in the current study) and the critical value ($\alpha=0.05$) was made to test the *Null* hypothesis. A p -value of 0.000 was reported by CMA and this value was also verified by using the command $f(x) = \text{CHIDIST}(1377.977, 57)$ on MS Excel. As the p -value is smaller than the level of significance (α) = 0.05, this allowed for the rejection of *Null* hypothesis which proposed that all studies shared a common effect size. This finding indicates that the true effect sizes in incorporated studies varied and that observed variation could not be completely ascribed to methodological errors in studies. This finding necessitated a further examination of effect size heterogeneity and potential moderation effects.

Procedures have been established in meta-analytic literature for estimating the heterogeneity in true effect sizes and heterogeneity arising from methodological errors (e.g., see Hedges & Olkin, 1985; Hedges & Vevea, 1998). This is because the observed heterogeneity in reported effect sizes comprises both true and spurious components, with the latter arising from random errors (Aguinis et al., 2011; Borenstein et al., 2009; Hunter & Schmidt, 2004). Hence, data for the Q -statistic and df was supplemented with other important statistics such as I -squared (presented in the Table 5.5). These measures provide insights on diverse aspects of data heterogeneity and enable an examination of dispersion in the true effect size values. Computations and findings pertaining to these heterogeneity estimates are now discussed.

5.3.2.2. Segregation and estimation of heterogeneity components

The fundamental premise of the RE model allows for variation in true effect sizes amongst incorporated studies (Aguinis, 2001; Aguinis et al., 2011; Borenstein et al., 2009; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001). In addition to the RE model premise, the rejection of the *Null* hypothesis (i.e., all studies have a common effect size) required further heterogeneity analyses.

The analyses were undertaken in order to estimate: 1. the variation in construct-level (i.e., true) effect sizes, and 2. the spurious variation stemming

from random errors. An estimate of heterogeneity between construct-level effect sizes can be obtained by computing the difference between the Q -statistic and df values (Aguinis et al., 2011; Borenstein et al., 2009). This follows because df represents the value of the Q -statistic under the premise that a common effect size underlies all studies and that the observed variation is purely a consequence of the sampling error (Borenstein et al., 2009). In other words, the df estimates the variation under an assumption that all studies share a common effect size. As mentioned earlier in the Chapter, the value of the Q -statistic represents the total (i.e., observed) variation in effect sizes. Therefore, the value of the heterogeneity estimate amongst true correlations (effect sizes) is calculated as follows:

$$\begin{aligned}\text{Heterogeneity (true)} &= \text{subtraction of } df \text{ from } Q\text{-statistic} = Q - df \\ &= 1377.977 - 57 = 1320.977\end{aligned}$$

$$\begin{aligned}\text{where, } df &= k - 1 \text{ (i.e., } k \text{ minus 1, where } k \text{ is the number of studies or} \\ &\text{independent samples)} = 58 - 1 = 57\end{aligned}$$

The true heterogeneity can also be represented via I -squared (or I^2). I^2 is the estimate of heterogeneity in the true effect sizes expressed as a proportion of total (observed) heterogeneity and computed by the formula:

$$\begin{aligned}I^2 &= (Q - df) / Q \times 100\% && \text{(Borenstein et al., 2009: 117)} \\ &= (1320.977) / (1377.977) \times 100\% \\ &= 95.864 \%\end{aligned}$$

A high I^2 value of 95.864 percent (also reported in Table 5.5) indicates that a large proportion of observed variation can be attributed to the heterogeneity amongst true effect sizes. The true heterogeneity value of 1320.977 (i.e., $Q - df$) is a standardised value like the Q -statistic and I^2 value of 95.864 percent is the estimate of true heterogeneity (i.e., $Q - df$) expressed as a percentage of total observed dispersion. Being a ratio, I^2 does not constitute an estimate of true heterogeneity *per se*.

The estimate of true heterogeneity can be converted into its original metric through simple mathematical formulae. The conversion of the true

heterogeneity estimate (i.e., $Q - df$) into measures such as Tau-squared and Tau is expected to facilitate a better understanding of true effect size dispersion, as these statistics are in the same metric as the effect sizes (Borenstein et al., 2009). Tau-squared is “variance of the true effects-sizes” (Borenstein et al., 2009: 114), and Tau is the standard deviation in the true effect sizes, and computed simply as the square-root of Tau-squared (Hedges & Olkin, 1985). The Tau-squared and Tau estimates enable an assessment of true effect size distribution just as variance and standard deviation provide information on the distribution pattern of primary-level data.

The calculations for the two statistics are not described here (for details, see Borenstein et al., 2009), because the CMA output reports the Tau-squared values alongside Q -statistic and df values, and is shown in Appendix-4. As the true effect size values are unknown, the reported Tau-squared and Tau values of 0.099 and 0.315 respectively are only estimates of the variance and standard deviation in true effect sizes. Thus, assuming a normal distribution (i.e., bell-shaped curve) of true effect size values, approximately 68% of effect size values are expected to lie between 0.064 (summary effect size minus Tau, i.e., $0.379 - 0.315$) and 0.694 (i.e., summary effect size + Tau = $0.379 + 0.315$). It can therefore be concluded that a considerable amount of variance may exist in the true effect sizes. The sub-group analyses for the hypothesised moderation effects are presented next.

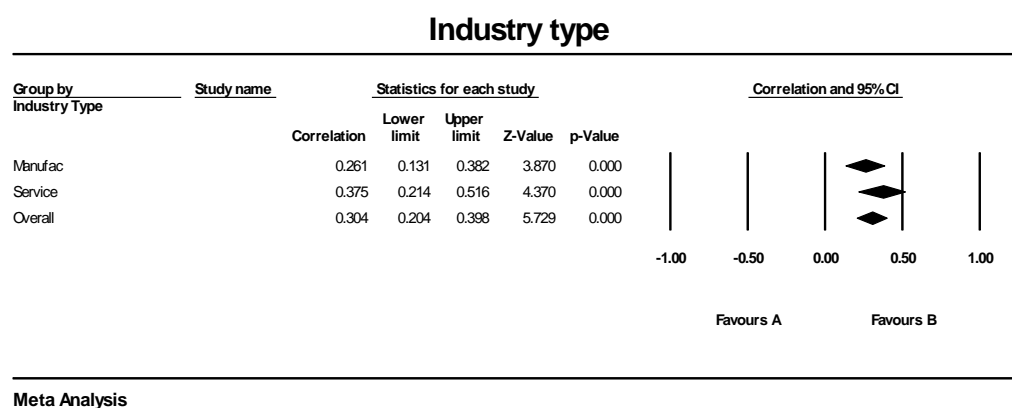
5.4. THE RESULTS OF MODERATION ANALYSES

5.4.1. Industry type

Thirty-one studies provided data on this moderator variable, exceeding the 10 studies heuristic for assessing moderation effects (discussed in Section-4.4). The summary effect sizes for this moderator variable suggest that the relationship under investigation is stronger for services than manufacturing firms. The summary effect sizes of the sub-groups for services and manufacturing are 0.375 and 0.261, respectively, with the CIs ranging from

0.214 to 0.516 and from 0.131 to 0.382. The Q -statistic value for between-group (manufacturing and service) difference was found to be 1.245 and the corresponding p -value 0.265 (see Appendix-5.a). The p -value is statistically non-significant, as it is higher than the level of significance ($\alpha=0.05$). Thus, the results of this sub-group analysis show that Hypothesis-2 is not supported and the prediction that PIC–firm performance relationship is moderated by industry type is unsubstantiated. The results of this sub-group analysis are summarised in Table 5.6, containing the forest plot in the extreme right. The overall (combined) summary effect size and effect sizes for each sub-group are represented by diamonds in the forest plot. The diamonds possess the same properties as outlined in Section-5.3 for the PIC–firm performance summary effect size.

Table 5.6: Moderation results for industry type



Appendix-5 provides screenshots of the relevant CMA Tables containing Q -statistics and p -values for all moderation effects examined in the current study.

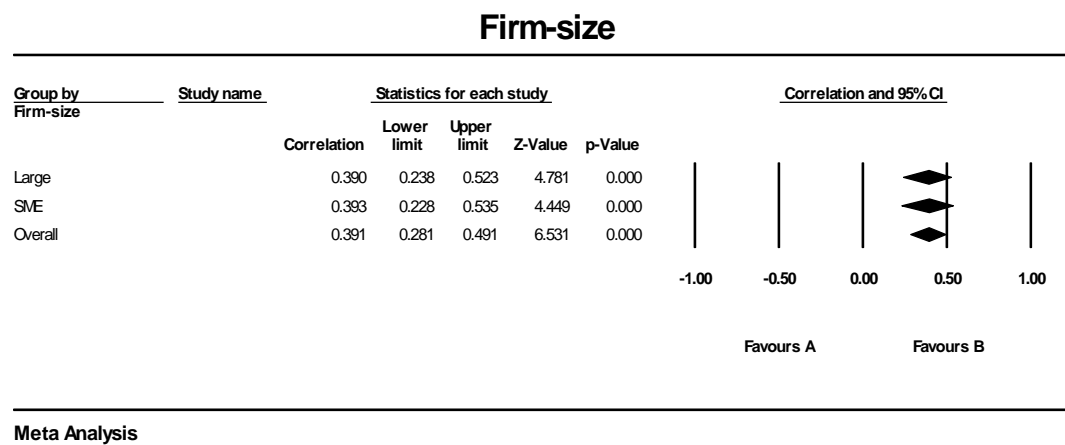
5.4.2. Firm size

Twenty-seven correlations were extracted and analysed from studies that focussed on either large or SME samples to detect the moderation effects of firm size on the relationship of interest. The summary effect sizes for the sub-groups of firm size are 0.390 and 0.393 for large firms and SMEs, respectively, with CIs ranging from 0.238 to 0.523 and from 0.228 to 0.535. The Q -statistic

value for between-group difference was found to be 0.001 and the corresponding p -value 0.982. The p -value is non-significant, as it is greater than $\alpha=0.05$ (see Appendix-5.b).

This result shows that Hypothesis-3, which predicted a potential moderation effect of firm size for PIC–firm performance relationship, is not supported. The relevant results are presented in Table 5.7 (also containing a forest plot).

Table 5.7: Moderation results for firm size

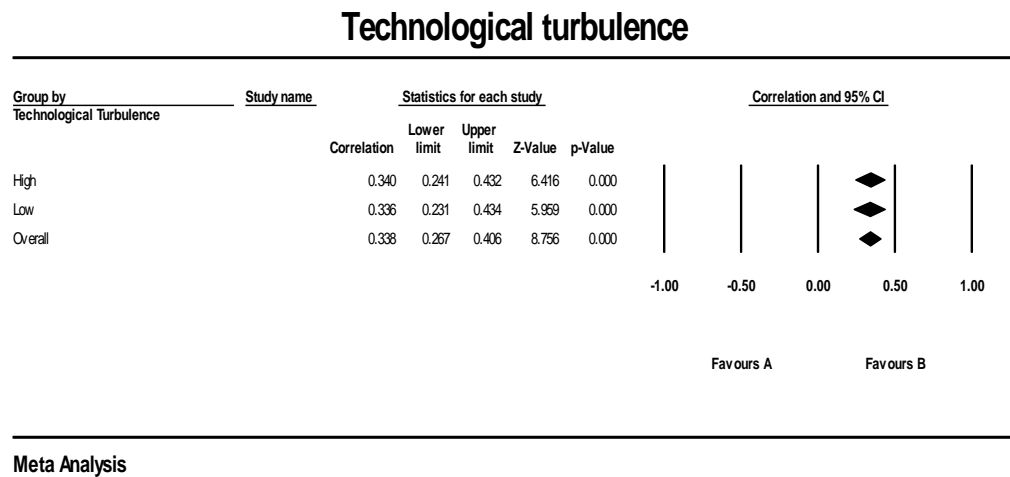


5.4.3. Technological turbulence

Forty five studies were coded for technological turbulence in accordance with the procedure described in Section-4.4. The summary effect sizes for high and low technological turbulence are 0.340 and 0.336, respectively, with CIs ranging from 0.241 to 0.432 and from 0.231 to 0.434. The summary effect sizes indicate that the relationship of interest is only incrementally stronger in the markets characterised by high rather than low turbulence. The p -value (for the Q -statistic value of 0.003) concerning the between-group (for high and low turbulence) difference in summary effect sizes is 0.955, which is statistically non-significant (being higher than $\alpha=0.05$) (see Appendix-5.c). Therefore, Hypothesis-4 is not supported. In other words, no statistically significant difference in the PIC–firm performance relationship is observed for different

levels of technological turbulence in the current study. The Table 5.8 (with forest plot) provides statistics regarding the sub-group analysis of technological turbulence.

Table 5.8: Moderation results for technological turbulence



5.4.4. Overview of moderations results

The Table 5.9 provides a summary of the results of the moderators examined through sub-group analyses.

Table 5.9: Summary of sub-group analyses

Moderator	Moderation Hypotheses	Findings
Industry type	H2: PIC–firm performance relationship is moderated by industry type	Statistically non-significant
Firm size	H3: PIC–firm performance relationship is moderated by firm size	Statistically non-significant
Technological turbulence	H4: PIC–firm performance relationship is moderated by technological turbulence	Statistically non-significant

5.5. OUTLIERS AND SENSITIVITY ANALYSES

As discussed in Section-4.7, an outlier analysis of the incorporated studies was performed, as such studies could cause the meta-analytic results (i.e., the summary effect size and heterogeneity estimates) to become skewed (see Cano, Carrillat & Jaramillo, 2004; Geyskens et al., 1998; Grinstein, 2008b; Kirca et al., 2005). Outlier sensitivity analysis involved the exclusion of five percent of the studies at each extreme of the effect size values (i.e., the three highest and the three lowest correlations in the current dataset). A meta-analysis on the remaining 51 studies (with 52 firm samples) was then performed. The six studies eliminated from the analysis were Eisingerich et al. (2009), O'Cass and Sok (2013b), Mithas et al. (2011), Richard et al. (2003), Penner-Hahn and Shaver (2005) and, Shoenecker and Swanson (2002). A meta-analysis with the remaining 51 studies yielded a summary effect size of 0.361 (with $CI_{95\%}$ ranging from 0.300 to 0.418), which is less than the value of 0.379 ($CI_{95\%}$ ranging from 0.305 to 0.448) obtained with the entire dataset. The small difference of 0.018 (i.e., $0.379 - 0.361$) in the two summary effect size values indicates that the six outlier correlations did not distort the meta-analytic results considerably.

Sensitivity analyses were also conducted to ascertain the impact of alternative methodological decisions on the results, as discussed in the Section-4.7. Specifically, alternative meta-analytic procedures and decisions tested for sensitivity analyses were:

1. the choice of Fixed-Effect (FE) versus Random-Effects (RE) model,
2. not having undertaken corrections for measurement errors, and
3. not having assigned adjustment factors to reported correlations via the weighting scheme.

The summary effect sizes obtained for these alternative decisions were 0.342, 0.321 and 0.348 respectively, all with significant p -values. These values are

smaller by 0.037, 0.058 and 0.031 from the summary effect size of 0.379, which was obtained with the choices of using a RE model, making corrections for measurement errors, and assigning adjustment factors to the reported correlations. The differences in values indicate a much greater effect of these choices, compared to the presence of potential outliers, in which case the difference was found to be lower (i.e., 0.018). Thus, it can be argued that the three choices had a considerable impact on the results, as was expected (discussed in Sections-4.2., 4.3. and 4.5.). To the best of knowledge, no statistic has been proposed in the meta-analytic literature to determine if the differences in the effect size values (obtained via sensitivity analyses), are statistically significant.

Further, a meta-analysis was conducted to ascertain a summary effect size with adjustments made to individual effect sizes on the basis of absolute (raw) employee numbers rather than their corresponding log-transformations. The use of absolute employee numbers represents the premise that firm size has a linear, rather than a curvilinear, relationship with resource commitments. The summary effect size obtained with raw data was 0.340 which is considerably smaller (by 0.039) than the value obtained for summary effect size with log-transformations. The difference indicates that the choice made between log-transformed and raw values on the basis of theoretical and empirical considerations was important, in the context of the adjustment made to correlations (see Section-3.3.2.).

5.6. PUBLICATION BIAS

Duval and Tweedie's trim-and-fill method and Rosenthal's *fail-safe N* were the methods used for assessing publication bias (i.e., the file drawer problem), as discussed in Chapter-4. Results of the Duval and Tweedie's Trim-and-fill method is discussed first followed by Rosenthal's *fail-safe N*.

5.6.1. Trim-and-fill method

Duval and Tweedie's method enables the generation of plots for visual assessment of the file drawer problem. In this method, there are two modes of funnel plot that are yielded by CMA. The plot for standard errors versus Fisher's z-transformations (of correlations) for the PIC-firm performance meta-analysis is presented in the Figure 5.1. The standard errors of studies are along the vertical axis and z-transformations are along the horizontal axis.

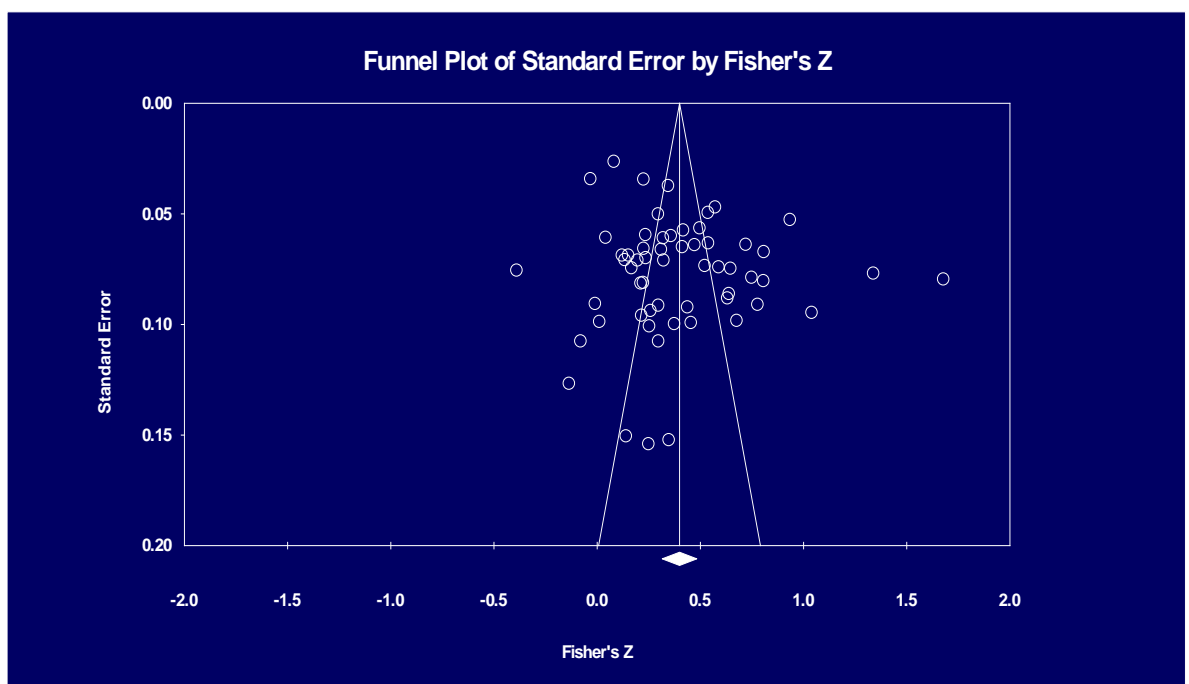


Figure 5.1.: Funnel plot for publication bias based on standard errors and z-transformations

A more commonly used form of the funnel plot is presented in the Figure 5.2, that plots study precision versus Fisher's z-transformations, along the vertical and horizontal axes, respectively. Precision of a study is the inverse of its standard error (Borenstein et al., 2009), which was used as the vertical axis in the previous Figure 5.1. Thus, for the sake of parsimony, and to avoid repetition, an interpretation of publication bias from the Figure 5.1 is made via comprehension of the Figure 5.2, as both Figures represent the same publication bias arising from the same dataset.

Studies that have relatively large samples and consequently greater precision, are plotted towards the top of the funnel plot. These studies are relatively closer to the centre vertical line (representing the summary effect size), than the studies that have relatively smaller samples (i.e., less precision), which appear towards the bottom of the funnel. As can be seen in the funnel, the latter (studies with smaller samples) are dispersed more widely around the summary effect size. In each plot, a diamond shape represents the summary effect size of 0.379 and the central vertical line splits the plotted values towards the left and right depending upon magnitudes of individual coordinates.

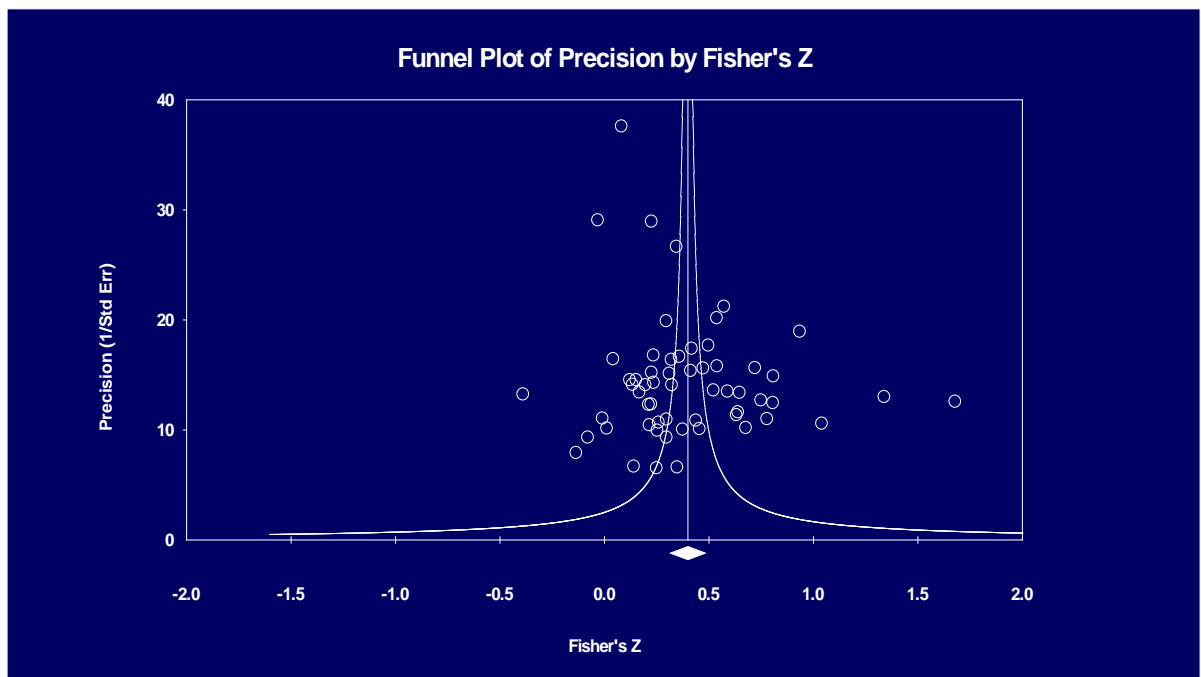


Figure 5.2.: Funnel plot for publication bias based on study precision and z-transformations

The Figure displays an asymmetrical distribution of studies around the summary effect size, thereby signifying the presence of publication bias. In the absence of bias, the funnel is symmetrical (Duval & Tweedie, 2000a; 2000b). The asymmetrical scatter of the studies shows a greater number of studies towards the left of the summary effect size. This raises a suspicion about the existence of studies that may actually fall towards the right of the

summary effect size but are missing from the dataset due to the possible presence of the file drawer problem.

The generation of a missing studies-adjusted summary effect size is also a major strength of Duval and Tweedie's trim-and-fill method, in addition to the generation of funnel plots. This estimate, as reported by CMA, which factors in potentially missing studies, is 0.474. This value indicates that in the absence of file drawer problem, the summary effect size would be 0.095 (i.e., $0.474 - 0.379$) higher than that obtained through the synthesis of incorporated studies. The value of missing studies-adjusted summary effect size, being higher than the summary effect size (as obtained via the current dataset), points to a potential absence of correlations representing a very strong association between PIC and firm performance. Thus, the true effect size of the PIC–firm performance relationship may actually be higher than what was found in the current meta-analysis.

5.6.2. Rosenthal's *fail-safe N*

Rosenthal's *fail-safe N* is the number of unpublished studies reporting null results required to render statistically significant findings non-significant (Rosenthal, 1979; 1995). The value obtained of *fail-safe N* was 27,030 studies. This value indicates that 27,030 studies reporting non-significant results would need to be incorporated in the current dataset to change the *p*-value from the value of less than 0.05 (level of significance), to greater than 0.05. In other words, incorporation of 27,030 correlations that are zero in value would be required to be included in the current dataset in order for the *p*-value to exceed the level of significance.

Using simple averages, 466 studies (i.e., 27,030 *fail-safe N* value, divided by 58 incorporated firm samples) reporting null results would have to be incorporated for each included study of the current dataset, to render the findings non-significant. It is extremely unlikely that such a high number of studies reporting correlations that are zero in value remained unpublished in the literature. Therefore, based on the assessment of publication-bias

undertaken through the trim-and-fill method and *fail-safe N*, it is concluded that although there is possibility of publication bias in the dataset, the statistically significant result pertaining to the summary effect size is substantive. Hence, there is very little reason to suspect that file drawer problem is inducing inordinate distortions in the meta-analytic findings. Thus, the significant PIC–firm performance relationship is supported.

5.7 CHAPTER SUMMARY

This Chapter presented the analyses of the coded data and the findings addressing the hypotheses developed in Chapter-3. The data-analysis and computational procedures conform to the research design and methodology presented in Chapter-4. The core findings of the analyses comprise the summary effect size, estimation of heterogeneity in true effects, assessing the presence of moderator variables, sensitivity analyses and the publication bias.

Sensitivity analyses were undertaken in order to estimate the results without potential outliers and with alternative meta-analytic decisions. The analysis of publication bias determined the extent to which the dataset may not accurately represent the entire body of empirical research (both published and unpublished) on the relationship under investigation.

The data-analyses were underpinned by meta-analytic conventions and scholarly prescriptions of the most appropriate computational procedures and their underlying assumptions, such as the adoption of the RE model. Importantly, the results were predicated on the adjustments (made to reported correlations) that account for the imperfect construct validity of PIC.

The summary effect size yielded by data-analysis demonstrates a strong link between PIC and firm performance, as hypothesised. However, no statistically significant moderation effects were found. The summary effect size and the results of sub-group moderation analyses are discussed alongside the implications and limitations of this study in the next Chapter-6.

CHAPTER SIX

DISCUSSION AND CONCLUSION

6.1 INTRODUCTION

The research presented in this dissertation involved critically analysing PIC construct validity for the purpose of investigating the direction and magnitude of the PIC–firm performance relationship, and ascertaining key boundary conditions for this relationship. Three specific research questions, developed from a review of the innovation and DC Theory literatures in Chapter-2, were addressed:

- 1. To what extent are PIC measures valid when examined using theoretical triangulation of complementary theories?*
- 2. What is the magnitude and direction of the true (construct-level) relationship between PIC and firm performance?*
- 3. Do industry type, firm size and technological turbulence moderate the relationship between PIC and firm performance?*

Underlying the PIC–firm performance meta-analysis (addressing the second and third research questions) was a theoretical triangulation analysis (focussing on the first research question). This analysis revealed a critical problem pertaining to the construct validity of PIC. In order to overcome this problem, a novel weighting scheme for adjusting correlations was devised and outlined in Chapters-3 and 4. The adjustments made to reported correlations aimed to factor in the efficiency dimension of PIC that has been largely

overlooked in the empirical literature. These adjustments attempted to enhance the construct validity of PIC, thereby enabling the computation of a superior estimate of the relationship between PIC and firm performance, and an assessment of its moderators.

Important methodological decisions, such as those concerning the computational procedures of the weighting scheme, the selection of a meta-analytic model and the summary effect size, were described in Chapter-4. The rationales underlying such decisions were discussed alongside the common meta-analytic protocols. Subsequently, Chapter-5 presented analysis of the dataset and results, such as those concerning the summary effect size, heterogeneity assessment, moderation and sensitivity analyses, and the file drawer problem.

This final Chapter discusses the meta-analytic findings and their implications, the potential limitations of the research, and highlights avenues for future research. Due to the centrality of the construct validity problem of PIC, and the methodological framework devised to address it, the current Chapter commences with a discussion of the adjustments made to correlations. This serves as a recap on the background for subsequent discussion of research question 1, as the foundation upon which the results pertaining to research questions 2 and 3 are built.

6.2. DISCUSSION OF EFFECT SIZE ADJUSTMENTS

The identified validity problem in PIC measurement provided the impetus for a key contribution of this study to the current body of knowledge, that is, the development of an effect size weighting scheme to enable adjustments to correlations. While an overwhelmingly large proportion of empirical research is unquestioningly patterned on measures that become sacrosanct once posited (Jacoby, 1978), the current study examined PIC measures (via triangulation) and presented a new methodology.

The formulation of the new weighting scheme was imperative for bridging the gap concerning oversight of the productivity dimension in operationalising PIC. The scheme enabled adjustments in individual correlations so as to assess the true magnitude of the construct-level relationship of interest, and not the magnitude of the relationship as represented by imperfect measures of PIC. This was achieved by offsetting the resource superiority advantage possessed by large firms of study samples and the resource disadvantage of small firms, before synthesising correlations.

The median of reported firm sizes was employed as the baseline for computing adjustment factors. This metric essentially worked as the threshold-level for determining relative resource advantage and disadvantage of large and small firms, respectively. The extent of the relative resource advantage or disadvantage was assessed on the basis of the magnitude of firm size deviation from the median.

Without the weighting scheme, the summary effect size would omit the PIC dimension concerning productivity of resource exploitation and, therefore, merely estimate the observed relationship between deficient measures of PIC, and of firm performance. The reason for calculating and assigning adjustment factors to individual correlations was to enhance the construct validity of PIC before synthesising the accumulated correlations.

6.3. DISCUSSION OF RESEARCH QUESTIONS

The findings regarding the assessment of PIC construct validity, summary effect size, moderation and sensitivity analyses, and the file drawer problem are discussed in this Section. This discussion links back to the fundamental aims of this study expressed in the research questions and the corresponding hypotheses (for the second and third research questions), as presented in Chapters-1 and 3, respectively. Owing to the exploratory nature of the first research question, no hypothesis was proposed.

6.3.1. Discussion of the first research question

Studies adopting multiple theoretical paradigms potentially make a greater contribution to innovation research through enhanced breadth of investigation (Wolfe, 1994). Substantial benefits of adopting a multi-theoretical approach (i.e., triangulation) for examining latent constructs have been demonstrated. In particular, triangulation has aided in overcoming the problem of domain-specificity that has eventuated in the fragmentation of the extant innovation literature (see Hauser, Tellis & Griffin, 2006).

Through triangulation, the current research conducted an examination of the degree of congruency between PIC conceptualisation and measurement. This facilitated a more comprehensive understanding of this central innovation and DC Theory construct, and its measurement models. The explanation of PIC from multiple theoretical lenses brought the construct validity of PIC into focus and addressed the first research question. The identification of an unspecified PIC dimension concerning the efficiency of resource utilisation was argued to be pivotal for the development of empirical literature on dynamic capabilities.

A few studies have focused on the congruency between the conceptualisation of innovation capability and its measures, and they did not adopt a one-size-fits-all approach for construct operationalisation, but were context-sensitive (e.g., Camisón & Villar-López, 2014; Hogan, Soutar, McColl-Kennedy & Sweeney, 2011). For example, while measures are available in the literature for operationalising innovation capability, Hogan et al. (2011) developed scale indicators that are of specific relevance (and arguably more valid) in the context of professional services. Thus, by addressing the first research question, the current study also complemented the research efforts focussed on construct validation of dynamic capability and innovation constructs.

The incorporation of the unaccounted for productivity dimension of PIC was asserted to be the solution for overcoming the validity problem in this study. In addition to theoretical triangulation, the *a priori* arguments (presented in the Section-2.3.4) concerning the exclusive use of effects measures confounding

innovation outcomes with relative resource allocations, constituted the impetus for this research.

Through the theoretical triangulation, this research provided a comprehensive evaluation of PIC construct validity. Such an appraisal paved the way for enhancing PIC validity and undertaking a substantive meta-analytic review of the relationship between PIC and firm performance. Hence, the second research question was a logical progression from the first, as it provided vital insights into the nature and extent of a fundamental problem. The second research question and its corresponding hypothesis are now discussed.

6.3.2. Discussion of the second research question and Hypothesis-1

The second research question concerned the magnitude and direction of the relationship between PIC and firm performance. The first hypothesis (H1) predicted a positive link between PIC and firm performance in accordance with theoretical arguments (see Schilke, 2014; Wilhelm et al., 2015). It is vital to consider H1 in light of the construct validity assessment, and the consequent adjustments made to the reported correlations for overcoming the identified problem of PIC validity. The summary effect size obtained through the synthesis of (adjusted) correlations served as an estimate of the magnitude and direction of the relationship of interest (Cohen, 1977, Lipsey & Wilson, 2001). Owing to the assignment of the adjustment factors to correlations, the summary estimate of the relationship is contended to be a substantive representation of the construct-level PIC–firm performance relationship. Therefore, the summary effect size is an empirical generalisation of the PIC–firm performance relationship (see Geyskens et al., 2009), and substantiates *a priori* contentions concerning the focal relationship.

H1 was supported: a positive relationship was found between PIC and firm performance. The results (i.e., the summary effect size and Confidence Interval) obtained by testing H1 indicate the significance of cultivating PIC for potentially attaining competitive advantage through the introduction of new products. Thus, the results corroborate and justify the emphasis in the

literature, on investigating the performance effects of introducing new products in the market (e.g., Grant, 1996a; Liu & Chen, 2015; Song & Montoya-Weiss, 2001).

The validation of H1 supports the core contentions of DC Theory that underscore a positive contribution of dynamic capabilities towards firm performance, and in the attainment of competitive advantage. This is a core finding of the PIC–firm performance meta-analysis. The magnitude of the summary effect size (i.e., 0.379) obtained for the relationship of interest is considerably stronger than that reported by Krasnikov and Jayachandran (2008) for PIC (as an overlapping construct with R&D capability) and firm performance (i.e., 0.275). As discussed in Section-2.6, R&D capability and PIC are not operationalised in the Krasnikov and Jayachandran (2008) meta-analysis as dynamic capability constructs. Therefore, the substantial difference in the magnitude of the summary effect sizes can be chiefly attributed to the operationalisation of PIC in the current study as a dynamic capability through the incorporation of the productivity dimension. The difference in the findings between the current study and Krasnikov and Jayachandran (2008) indicates that dynamic capabilities potentially confer greater performance benefits versus operational capabilities.

In addition to determining a generalisable PIC–firm performance relationship, the meta-analysis aimed to delineate the boundary conditions of the relationship. Hence, three theory-derived moderators were examined, and the results of the sub-group moderation analyses are discussed next.

6.3.3. Discussion of the third research question and Hypotheses-2 to 4

Sub-group analyses were conducted in compliance with the recommendations of meta-analysis scholars (e.g., Aguinis et al., 2011; Borenstein et al., 2009). A qualification concerning the use of *p*-values needs to be made here with regards to interpretation of all moderation results in the study. While the statistically non-significant *p*-values (concerning the differences in summary effect sizes) in sub-group analyses indicate that moderation effects are absent,

non-significant p -values may also imply insufficient statistical power (Borenstein et al., 2009). While the latter possibility of low statistical power cannot be completely ruled out, the analyses conducted comply with the minimum 10-study heuristic for the explication of moderation effects (as discussed in Section-4.4). Against the backdrop of the preceding caveat, the results obtained for each moderation analysis are discussed here.

6.3.3.1. *Industry type*

Results did not support moderation of the PIC–firm performance association by industry type. Hence, H2 was not supported. However, judging by the heuristics proposed by Cohen (1977), the summary effect size for services (i.e., 0.375) was considerably greater than the summary effect size for manufacturing (i.e., 0.261). The magnitude of difference in summary effect sizes indicates the distinct possibility that a stronger relationship is likely to exist between PIC and performance in the service sector rather than the manufacturing industry. These results are novel owing to: 1. the relationship of interest not having been meta-analytically examined yet for the moderating role of industry type, and 2. individual correlations being adjusted to account for relative resource inputs.

Therefore, notwithstanding the results being statistically non-significant, they provide insights into the moderating role of industry type through the indication of a potentially stronger relationship in the service industry. Due to the considerable difference in the summary effect sizes obtained for the service and manufacturing industries, the *a priori* expectation that the characteristics of the market offerings (e.g., tangibility and variability), potentially moderate the PIC–firm performance relationship, appears plausible.

The results obtained are somewhat consistent with those reported in two other meta-analyses, namely, Krasnikov and Jayachandran (2008) and Vincent et al. (2004). These studies also reported non-significant moderation effects of industry type on the relationships between R&D capability– and

innovation–firm performances, respectively. It is important to highlight here that any direct cross-study comparisons can be misleading owing to the multidimensionality of and differences in the operationalisation of innovation constructs (see Downs & Mohr, 1976; Van de Ven & Rogers, 1988). It is important to be mindful of such potential fallacies, even if the moderation results are being compared across meta-analytic studies. This is asserted because the operationalisations of constructs in meta-analyses are generally contingent upon and conform to measurement models deployed in the incorporated studies (see Camisón-Zornoza et al., 2004). Therefore, the moderation effect of industry type reported in Krasnikov and Jayachandran's (2008), Vincent and colleagues' (2004) and the current meta-analyses, should be compared with caution via factoring in the measurement approaches used.

6.3.3.2. *Firm size*

Hypothesis-3, that the PIC–firm performance association is moderated by firm size, was not supported. The summary effect sizes for the two sub-groups, large firms versus SMEs, revealed a negligible difference in the magnitude of the relationship. As the Confidence Intervals of the two groups were also largely overlapping, the results clearly suggest that regardless of firm size, the association of PIC to firm performance is virtually identical.

The sub-group analysis for large firms versus SMEs enhances the understanding of the moderation effects of firm size. As discussed in Chapter-3, the scholarly community is divided with regards to whether firm size (i.e., large firms or SMEs) is an important determinant of innovation and its association with firm performance (see Acs & Audretsch, 1987; Aiken & Hage, 1971; Audretsch & Acs, 1991; Damanpour, 1991; 1992; Hage, 1980; Jervis, 1975; Rosenbusch et al., 2011; Rubera & Kirca, 2012; Schumpeter, 1934; 1942; Verhees & Meulenbergh, 2004). The moderation analysis was undertaken to provide insights into the inconclusive empirical findings and help resolve contradictions in theoretical arguments. The *a priori* arguments in the literature are largely centred on relative resource/capability possession,

risk-taking ability, flexibility and agility of large versus SME firms (Camisón-Zornoza et al., 2004).

Indeed, the firm size moderation results obtained in the current study are important, primarily for the reason as they indicate that both large firms and SMEs are equally adept in capitalising on product innovation in terms of garnering performance benefits. This finding sheds light on the intense debate in the literature on whether large firms are better placed versus SMEs to yield and capitalise on product innovations. It is therefore concluded that the perceived advantages and disadvantages of greater firm size largely balance-out so that the hypothesised advantages of large firms are completely neutralised by the advantages possessed by their SME rivals.

It is however possible that measures of firm size not employed in this research (e.g., sales revenue and total firm assets), may produce different results for sub-group analyses. In other words, some disparity in the summary effect sizes of large and SME firms could be observed by using alternative firm size measures (e.g., see Camisón-Zornoza et al., 2004). This is possible because firm size is a multidimensional construct and different measures can capture different dimensions of the variable to varying extents (Gooding & Wagner, 1985; Kimberly, 1976). Sub-group analyses with alternative measures were not conducted in this study due to: 1. the difficulty in operationalising firm size via other measures due to data availability constraints, 2. the appropriateness of the number of employees as a valid measure of firm size (Child, 1973b).

6.3.3.3. Technological turbulence

The results of sub-group analysis for moderation effect of technological turbulence were statistically non-significant for low- and high-levels of the variable. Thus, Hypothesis-4 was not supported. The lack of moderation indicated by the sub-group analysis in this study are similar to that obtained by Song et al. (2005) for technological turbulence as a moderator of technological capability–firm performance association. They report similar

levels of technological capability and firm performance association, under both low- and high-degrees of technological turbulence. This was contended because technological capability is explicitly modelled by Song et al. (2005) as subsuming PIC as a core component. Similarly, in relation to low- and high-levels of market dynamism (encompassing technological turbulence), Protojerou et al. (2012) reported comparable levels of dynamic capability and firm performance association. Such findings, in conjunction with the results of the moderation analyses reported here, suggest that the relationship of dynamic capabilities with firm performance may largely be the same, regardless of the level of technological turbulence (and market dynamism) prevailing in the market.

Although an examination of the moderation effects of technological turbulence on the relationship between capabilities and firm performance has been urged by scholars (e.g., Krasnikov & Jayachandran, 2008), few studies have actually investigated this. Technological turbulence is a potential substantive moderator in and of itself, and it was also deployed as a proxy for market dynamism in this study. The justification for inferring a moderation impact for market dynamism from a direct investigation of technological turbulence was discussed in the Section-2.4. Thus, the result obtained through sub-group analysis of technological turbulence is also interpreted in relation to the broader market dynamism construct in the current study.

Given the centrality of influence exerted by market dynamism on the dynamic capability–firm performance relationship, as proposed in DC Theory literature (see Barreto, 2010; Eisenhardt & Martin, 2000; Wang & Ahmed, 2007), deducing its moderating effect via inferential reasoning is a contribution of the present study. As already stated, the assessment of the moderating effect of market dynamism on the PIC–firm performance association was obtained via a direct examination of moderation by technological turbulence. Secondary data sources were used to operationalise technological turbulence (e.g., see Wilhelm et al., 2015). Meta-analyses have the ability to examine moderators regardless of whether they have or have not been investigated in primary studies (Damanpour, 1992; Guzzo et al., 1987). This moderation analysis also

helped to overcome a limitation of the meta-analysis conducted by Krasnikov and Jayachandran (2008). While encouraging a meta-analytic investigation of the moderating effect of market dynamism, Krasnikov and Jayachandran (2008: 8) state (regarding their study) that:

It is not feasible in the context of this study to determine whether the dynamic nature of the market affects the relative association of different capabilities with performance.

The current study contributes by demonstrating that this perceived limitation of meta-analytic methods can potentially be overcome through data acquired from secondary sources (e.g., The International Monetary Fund, The World Bank) and the use of appropriate proxy measures.

As alluded to earlier in this Chapter, in relation to the interpretation and comparison of moderation effects of technological turbulence across studies, it is important to bear in mind that PIC has been modelled differently (and more comprehensively) in the present study than in previous efforts (e.g., Delgado-Verde et al., 2011; Grawe et al., 2009; Krasnikov & Jayachandran, 2008). Any direct comparisons of moderation results (obtained in this study) with the results of other studies should be qualified, as the PIC operationalisation in this study varies from others. The theoretical and practical implications of the study stemming from summary effect size and moderation analyses of the focal relationship are discussed in the following Section.

6.4. IMPLICATIONS FOR THEORY AND PRACTICE

This study has expanded the existing body of knowledge by conducting a PIC–firm performance meta-analysis, underpinned by a theoretical triangulation between DC, Process Management and Ambidexterity Theories. The research has demonstrated that the operationalisation of dynamic

capabilities and multi-dimensional innovation constructs must be examined thoroughly (see Calantone et al., 2010; Vogel & Güttel, 2013; Wang et al., 2015; Wolfe, 1994; Zahra et al., 2006). Researchers must be cognizant of the need to attain high validity of measurement, which constitutes the foundation on which all of scientific inquiry is predicated (Thorndike & Hagen, 1977). Peter (1981: 133) similarly states that, “construct validity is a necessary condition for theory development and testing”. Hence, it is argued that notwithstanding the sophistication of computer programs (for data-analysis) that are currently in widespread use, research findings can be called into question if the construct validity of the measures used is compromised. The often mentioned problem of conceptual vagueness in the dynamic capability constructs (see Wang et al., 2015; Zheng et al., 2011), is (partly) resolved by the triangulation employed in this study, because it provided a better understanding of PIC as a dynamic capability. An inability (or failure) to clearly conceptualise the constructs under investigation severely constrains the development of empirical research, making the hypotheses and empirical findings of studies highly questionable (MacKenzie, 2003). This study has shown that when the constructs are more clearly conceptualised, with all dimensions explicitly spelled out, the validity of measures can be enhanced to ensure generation of substantive findings.

The introduction of an effect size adjustment methodology is also an important contribution of the study. The methodology has strong implications for empirical research and potentially enhances the extent of meta-analytic applications. The generation of a summary effect size of the focal relationship and the assessment of its moderation by industry type, firm size and technological turbulence, are amongst the key contributions of the study. Importantly, this study adheres to a primary objective of meta-analytic reviews which is to evaluate construct-level relationships, and not merely the observed relationships that are represented by deficient measures of constructs (Hunter & Schmidt, 1990; 2004; Schmidt & Hunter, 1996).

By identifying a validity problem in PIC measurement, the study offers a gateway for the development of more valid measures of PIC in particular, and dynamic capabilities in general. This is because, PIC is a dynamic capability

and many dynamic capability constructs are expected to exhibit certain commonalities in their multidimensional conceptions (see Barreto, 2010). Thus, the productivity dimension of PIC is applicable for some other dynamic capabilities as well, and the incorporation of this dimension in measurement models of other dynamic capability constructs can enhance their validity. This has vital implications for empirical research in DC Theory, as the deployment of valid measures is a pre-requisite for scientific enquiry (Cronbach, 1971; Nunnally, 1967; Peter, 1981). Therefore, the implications of the current study transcend the scope of traditional meta-analyses, which do not undertake a review of construct validity and consequently, do not carry out effect size adjustments to enhance it.

Owing to the fact that PIC is an important focal point for research in both the DC Theory and innovation literatures, the current study contributes to and enriches existing knowledge along multiple trajectories. Garcia and Calantone (2002: 111) state that “for empirical research to have an impact on practice, it should be focused, clear and report ‘true’ differences...”, and the present meta-analysis fulfils such pre-requisites for practicality. Underpinned by a clear focus on the validity of PIC measurement and its relationship with firm performance, the study has significant implications for management practitioners. For example, by facilitating a deeper understanding of the PIC–firm performance relationship through provision of insights concerning moderators, the study yields practical findings. Developing PIC appears to be an imperative for firms in order to secure superior performance and industry practitioners must commit themselves to fostering this key dynamic capability. PIC can be cultivated by simultaneously pursuing both exploratory activities, and process management techniques (such as Six Sigma and Total Quality Management), as indicated by the present research and also alluded to by other studies (e.g., see Day, 2011). The moderation analyses demonstrate that, regardless of firm size and industry type, the association between PIC and firm performance remains strong. Thus, fostering PIC is critical for SMEs and large firms, and also for both service and manufacturing firms. Furthermore, moderation results indicate that the focal relationship is strong irrespective of whether a firm is operating in conditions characterised by a low

or a high degree of technological turbulence. This finding has implications for managers in the sense that it highlights the importance of cultivating and possessing key dynamic capabilities under different conditions of technological turbulence.

The focus of this study on the productivity dimension of PIC also has implications for practitioners, as it brings the application of Process Management techniques into the spotlight. The study highlights the pivotal contribution that Process Management can make in efficiently managing product innovation activities. In this regard, it is asserted that the productive utilisation of resources must not be allowed to be crowded out by exploratory activities, and a simultaneous emphasis on both exploitative and exploratory activities concerning product innovation is a key to success. This notion cautions managers against the exploration trap in addition (and in contrast) to the exploitation trap. Balancing exploitation and exploration constitutes the core of Ambidexterity and it has received considerable scholarly attention in the innovation, DC Theory, knowledge management and Ambidexterity literatures (e.g., see Danneels, 2008; Levinthal & March, 1993; March, 1991; Oshri, Pan & Newell, 2005; Raisch & Birkinshaw, 2008; Sirén et al., 2012). The caveat of exploration trap substantiates the central Ambidexterity tenet of achieving a “trade off between business efficiency and the innovative capability” (Trott & Hoecht, 2004: 367) and “maintaining an appropriate balance between exploration and exploitation” March (1991: 71). In other words, this study supports the caveat of losing the optimal balance between exploration and exploitation as an inordinate emphasis by practitioners on the former can diminish focus on maximising resource exploitation.

Consequently, the managers in charge of product innovation processes must be very mindful of using Process Management techniques as they not only aid in productivity enhancement, but also have demonstrable benefits for product quality improvements (see Anderson, Rungtusanatham & Schroeder, 1994). Although in widespread acceptance, a greater use of Total Quality Management, Statistical Quality Control and Six Sigma methods, which largely originated from Process Management (see Benner & Tushman, 2002),

particularly in new product development is strongly recommended to enhance both process efficiency and the quality of new products.

Furthermore, the findings of this research are likely to assist managers in benchmarking dynamic capabilities possessed by their firms, in relation to competing firms in the market. This is because the identification of the efficiency (of resource utilisation) dimension of PIC can enable a comparative appraisal and benchmarking of dynamic capabilities across firms (e.g., see Wang et al., 2015). Benchmarking is the learning-oriented process of identifying, appraising and emulating competitors' practices for enhancing business performance (Zairi, 1998). The literature suggests that benchmarking of capabilities can lead to superior performance (e.g., Grant, 1996b, Vorhies & Morgan, 2005). Thus, a clear focus on the productivity dimension of PIC can aid in identifying and implementing process management techniques (followed by rival firms), that have been demonstrated to have contributed towards firm performance gains, via new product introductions.

The identification of the efficiency dimension also contributes to the discussion in the literature concerning the extent of idiosyncrasies and commonalities that dynamic capabilities exhibit across different firms (see Denford, 2013; Eisenhardt & Martin, 2000; Wang & Ahmed, 2007; Wang et al., 2015). Indeed, Wang and Ahmed (2007: 31) state that, "commonalities have not been systematically identified". Additionally, the efficiency dimension can facilitate further research on DC Theory, as the determination of commonalities between dynamic capabilities can aid in the empirical testing and expansion of the theory (e.g., see Drnevich & Kriauciunas, 2011; Eisenhardt & Martin, 2000; Wang & Ahmed, 2007; Wang et al., 2015). For example, the identification of another common feature (i.e., the efficiency dimension), "encourages cross-comparison of research findings" (Wang & Ahmed, 2007: 32); because it offers a yardstick for making comparisons between the empirical results of studies investigating PIC.

In offering a more comprehensive viewpoint for calibrating PIC as a dynamic capability construct, the study also answers the call by Krasnikov and

Jayachandran (2008). These authors urge undertaking research efforts that factor in the intricacies of operationalising higher-order (dynamic) capability constructs. As the empirical literature on DC Theory is relatively scarce, intensive efforts must be undertaken to bridge this deficiency (e.g., Cepeda & Vera, 2007; Morgan et al., 2009; Newbert, 2007; Vogel & Güttel, 2013). Cepeda and Vera (2007: 426) specifically highlight the lack of an integrative framework on DC Theory and observe that, “there has been little effort to consolidate findings in a unifying picture”. As little research has been undertaken to address this gap, this study contributes towards consolidating DC Theory through a synthesis of scattered findings, with PIC modelled as a dynamic capability. This study is the only attempt thus far to meta-analytically investigate the relationship of a prominent dynamic capability with firm performance.

The study demonstrates that all facets of dynamic capability and innovation constructs must be clearly and explicitly defined to ensure that these dimensions are appropriately represented in measures. Camisón-Zornoza et al. (2004: 334) highlight the imperative of accurately defining multidimensional constructs (e.g., PIC), and state that:

It must be borne in mind that defining a multidimensional concept is not only a question of literary synthesis, far more important is the fact that the definition must include all the theoretical dimensions implicit in the construct.

Thus, a comprehensive and multidimensional definition of dynamic capability constructs can enable the development of congruent measurement models. Consequently, high construct validity for dynamic capability constructs would be attainable. It is further recommended that research on dynamic capability and innovation constructs must use operational definitions, in addition to theoretical definitions of constructs (see Forza, 2002; Kohn & Jacoby, 1973). This is suggested as operational definitions tend to spell out the implicit dimensions and validation procedures of constructs (Forza, 2002; Vandervert, 1988).

Scholars have underscored the ability of meta-analyses in assessing validity through the incorporation of studies spanning diverse contexts and methodological procedures (e.g., Hall, Tickle-Degnen, Rosenthal & Mosteller, 1993; Krasnikov & Jayachandran, 2008). This study demonstrates that the value of meta-analyses goes well beyond the ability to evaluate construct validity, and shows that meta-analyses can also enable validity enhancement through *post hoc* effect size modifications. This is argued because the weighting scheme used is a unique methodology and such an endeavour to enhance construct validity of either independent or dependent variables before statistical aggregation has not been undertaken in management literature. Hence, by offering a broadly applicable and robust perspective for understanding and operationalising dynamic capabilities, the study has implications for both researchers and practitioners.

6.5. POTENTIAL LIMITATIONS

Notwithstanding the multifarious contributions of the study to the existing body of knowledge, the meta-analytic results reported need to be interpreted in light of certain caveats and limitations. Some limitations stem from trade-off decisions that are required in virtually all meta-analyses in social sciences such as the choice to either reject or accept studies for inclusion, which do not report reliability estimates. Such decisions often entail the use of methods that approximate missing values rather than dropping the study from inclusion altogether. For the sake of brevity, the research design and methodological decisions that are unique to this study and to meta-analyses are focussed on here. Such decisions and their outcomes could have resulted in some distortions in the research findings.

6.5.1. Industry representativeness of incorporated firm samples

Different levels of emphasis on innovation activities by different firms and industries are likely to be contingent upon several factors such as the nature of products offered by a firm, technological turbulence and competitiveness

prevailing in an industry, amongst others (e.g., see Han et al., 1998; Hurley & Hult, 1998; Song et al., 2005). Such factors collectively dictate resource allocations towards product innovation and so result in such allocations across firms to be disparate. The potential disparity in resource allocations was considered in this study in light of firm size, which was used as a proxy for resources committed towards product innovation. However, if highly innovation-intensive firms are compared directly with the firms characterised by relatively low innovation intensiveness, the use of firm size as a proxy may have caused under- or over-estimation, respectively, of relative resource allocations. However, considering that most of the studies used in the meta-analysis investigated firm samples from a broad spectrum of industries, any cumulative skewness in the results of this study should have been small. This is because a large proportion of the sample encompassed both high and low innovation-intensive industries and so any under- and over-estimation of resource allocations (consequent to the use of firm size as proxy) should have balanced-out.

6.5.2. Imperfect validity and lack of perfect congruency in PIC measures

Although many researchers have emphasised the absence of congruency in the measurement of innovation constructs, scant attention has been paid to validity in the innovation literature (see Garcia & Calantone, 2002; Montoya-Weiss & Calantone, 1994). Despite construct validity being a core theme in the current research, the study does not claim to operationalise PIC perfectly; imperfect construct validity might still persist (albeit to a much lesser degree) even after effect size adjustments. The weighting scheme employed in the study chiefly concerned enhancing the construct validity of PIC and not perfecting it, as latent multidimensional constructs are difficult to measure comprehensively (see Mackenzie et al., 2005). This contention is reflected in an insightful comment by Hunter and Schmidt (2004: 42) that “construct validity is a quantitative question, not a qualitative distinction such as ‘valid’ or ‘invalid’; it is a matter of degree”.

While the present study aimed to overcome the construct validity problem of PIC through a meta-analysis, it may still have been influenced to some degree

by imperfect validity of PIC measurement in the individual studies that were used. Nevertheless, it is argued that by virtue of the attempt to enhance the validity of PIC *post hoc*, the present research is constrained by imperfect validity to a far lesser degree than the primary studies incorporated in the meta-analysis. Furthermore, absolutely identical conceptualisations and operationalisations of PIC across studies were hardly ever observed in the literature, bringing validity issues into focus yet again. For the present study, the lack of perfect congruency in PIC and firm performance operationalisations across incorporated studies can also be a source of imperfection in the results. However, this can be contended to be a common limitation of most meta-analyses in social sciences, as latent constructs (e.g., PIC) frequently differ in their operationalisation, especially when measured across multiple industries (Krasnikov & Jayachandran, 2008).

6.5.3. General limitations of meta-analytic reviews

Meta-analyses are often restricted by a lack of full disclosure and of methodological errors (e.g., sampling and measurement errors) contained in empirical studies (Hunter & Schmidt, 1990); the current study is no exception. The frequent unavailability of data (from incorporated studies) pertaining to reliability estimates and to the size of sampled firms may cause minor imperfections in the current meta-analytic dataset, despite the measures undertaken to minimise their impact (discussed in Sections-4.3 and 4.5). In addition, the use of *average* number of employees as the metric for firm size (in the weighting scheme) may have caused a degree of range restriction in the dataset. This potential problem of range restriction could not be overcome, as individual firm-specific values of the number of employees were not reported in any incorporated study, necessitating the use of averages. This underscores the fact that meta-analyses are generally restricted by the reporting practices of empirical research (see Hunter & Schmidt, 2004).

Some researchers have questioned the degree to which meta-analyses are objective. For example, DeCoster (2009: 3) opines that “meta-analysis provides an opportunity for shared subjectivity in reviews rather than true objectivity”. It can be argued that such assertions essentially underscore

certain qualitative decisions and interpretations that are generally unavoidable in an extensive and multifaceted statistical methodology like a meta-analytic review. For example, subjectivity is difficult to completely eliminate from study inclusion and coding, especially when the task is very complex, and it manifests itself in disagreements amongst individual coders. While the current meta-analysis may possibly contain a degree of subjectivity, it is likely to be a source of error only to the extent that subjectivity may distort results in incorporated studies, and not more. This is maintained because of the objective nature of the coding task in the current study and the accuracy of data-coding (discussed in Section-4.4). Furthermore, virtually all the meta-analyses conducted in management (as also the current PIC–firm performance meta-analysis), are likely constrained by not having incorporated all relevant published studies. This potential limitation was also outlined in Section-4.4 (on data collection).

Notwithstanding some limitations of meta-analyses as outlined here, it is widely acknowledged that meta-analytic results are more generalisable than the results reported in individual studies (Damanpour, 1992; Geyskens et al., 2009). Via statistical aggregation, heterogeneity and moderation analyses, as well as corrections for errors (amongst others features), meta-analyses afford a superior understanding of the phenomena under investigation (see Borenstein et al., 2009; Cooper, 2010; Hunter et al., 1982; Viswesvaran & Ones, 1995). Thus, it is claimed that despite potential limitations, this study significantly expands the current knowledge base and opens several exciting avenues for further research. Research opportunities that can, in particular, advance DC Theory and innovation literatures are discussed next.

6.6. AGENDA FOR FUTURE RESEARCH

This research offers multiple pathways for guiding future research efforts. First and foremost, future research can focus on elimination of the deficiencies in

the conceptualisation and measurement of dynamic capability constructs, using the theoretical triangulation approach presented in this study. The efficiency gap identified in PIC measurement can spur research efforts that are driven by validity enhancement, and encompass scale development for dynamic and operational capability constructs. Scale development for capability constructs offers a fertile ground for further research endeavours as demonstrated by some recent research (e.g., see Hogan et al., 2011).

It is recommended that researchers consider the inclusion of measures that combine effects and input measures of PIC concurrently, in a manner that captures the productivity dimension. Effects and input measures are the two extremities (process end-points) that are required to factor in the efficiency dimension of capabilities. The underlying rationale of the recommendation is that the productivity of a process can be accounted for through a ratio of resource input and effects measures.

A recent study by Camisón and Villar-López (2014) recognises the resource productivity dimension of innovation capability via deployment of measures that focus on efficiency. The study incorporates scale indicators such as “my firm organises its production efficiently” and “my firm assigns resources to the production department efficiently” (Camisón & Villar-López, 2014: 2900), suggesting that some researchers have begun to employ measures that aim to factor in the productivity dimension.

As stated earlier, future research in DC Theory and innovation should be driven by the recognition of construct validity as a focal point for theory testing and expansion of empirical research. Several studies, many of them published decades ago, offer prescriptions for ensuring substantive testing of theories in order to yield practical implications for both practitioners and researchers (e.g., Jacoby, 1978; Nunnally 1967, Peter, 1981; Thorndike & Hagen, 1977). Research must also focus on further improving the conceptualisation of dynamic capability constructs to minimise vagueness and tautology (see Priem & Butler, 2001; Williamson, 1999), as attempted using theoretical triangulation in this study. Indeed, poor conceptualisation results in measurement errors (Danneels & Kleinschmidt, 2001; Mackenzie, 2003).

A recurrent theme of the study was the process-based conception of PIC as a dynamic capability. This conception necessitated the concurrent consideration of resource inputs and effects measures in PIC operationalisation. Such an operationalisation approach can potentially be extended to operational capabilities. This contention is predicated on the conception and operationalisation of operational capabilities as also being grounded in processes (e.g., see Bharadwaj, 2000; Cepeda & Vera, 2007; Kozlenkova, Samaha & Palmatier, 2013; Morgan et al., 2009). As the weighting scheme in the current study was underpinned by the process-based conceptualisation of PIC, it is potentially deployable in meta-analyses investigating relationships between operational capabilities and firm performance, thereby offering further research opportunities. Additionally, empirical research centred on operational and dynamic capabilities can benefit considerably from intensive application of Process Management, as demonstrated in the present study (see Benner, 2009; Benner & Tushman, 2003).

Owing to the detailed provision and description of computational procedures (referred to as best practice by Aguinis et al., 2011) in this study, the PIC–firm performance meta-analysis can be replicated and extended by researchers in the future. For example, meta-analyses such as Damanpour (1992) and, Henard and Szymanski (2001) have been replicated and expanded by Camisón-Zornoza et al. (2004) and Evanschitzky et al. (2012), respectively. Replication of meta-analyses can enable comparison of results from different time spans and provide diverse scholarly views on the same subject (Camisón-Zornoza et al., 2004). Specifically, while this meta-analysis examined moderators identified *a priori*, investigation of the methodological/contextual characteristics of studies as moderator variables can also generate useful findings (e.g., see Rosenbusch et al., 2011; Vincent et al., 2004). A statistical aggregation of studies covering different temporal periods and country/industry contexts from the ones focused on in the current study can generate additional insights.

6.7. CONCLUSION

The contention made by Wolfe (1994: 406) more than two decades ago that “there can be no *one* [emphasis in original] theory of innovation, as the more we learn, the more we realise that ‘the whole’ remains beyond our grasp...” is evidently still valid today. This notion of theoretical diversity in innovation research is exemplified by this thesis (see Downs & Mohr, 1976; Van de Ven & Rogers, 1988; Wolfe, 1994). By expanding the existing knowledge base, the research has contributed to the need for intensive research efforts to consolidate innovation and DC Theory literatures.

Specifically, the research enabled advancement of theoretical and empirical literature along multiple trajectories through the identification and elimination of a validity problem that has persisted in PIC operationalisation, by undertaking a statistical synthesis of adjusted correlations that overcomes this problem, and providing insights into the moderators of the PIC–firm performance relationship. In doing so, the research makes a significant contribution to core discourses in the innovation and DC Theory literatures.

REFERENCES

- Abrahamson E. (1991) "Managerial fads and fashions: The diffusion and rejection of innovations". *Academy of Management Review*, 16: 586–612.
- Acs Z.J and Audretsch D.B. (1987) "Innovation, market structure, and firm size" *The Review of Economics and Statistics*, 69(4): 567–574.
- Adler P. S. and Shenbar A. (1990) "Adapting your technological base: The organizational challenge" *Sloan Management Review*, 25: 25–37.
- Agarwal R. and Selen W. (2009) "Dynamic capability building in service value networks for achieving service innovations" *Decision Sciences*, 40(3): 431–475.
- Agarwal R. and Selen W. (2011) "Multidimensional nature of service innovation" *International Journal of Operations & Production Management*, 31(11): 1164–1192.
- Aguinis H., Gottfredson R.K. and Wright T.A. (2011) "Best-practice recommendations for estimating interaction effects using meta-analysis" *Journal of Organizational Behavior*, 32: 1033–1043.
- Aguinis H. and Pierce C.A. (1998) "Testing moderator variable hypotheses meta-analytically" *Journal of Management*, 24(5): 577–592.
- Aiken M. and Hage J. (1971) "The organic organization and innovation" *Sociology*, 5(1): 63–82.
- *Akgün A. E., Keskin H. and Byrne J. (2009) "Organizational emotional capability, product and process innovation, and firm performance: An empirical analysis" *Journal of Engineering and Technology Management*, 26(3): 103–130.
- Alam I. (2011) "Exploring cross-national differences in service innovation process and strategy in developing and developed nations" *Journal of Service Management*, 22 (5): 586–606.
- Ancona D. G., Goodman P. S., Lawrence B. S. and Tushman M. L. (2001) "Time: A new research lens" *Academy of Management Review*, 26: 645–663.
- Anderson J. C., Rungtusanatham M. and Schroeder R. G. (1994) "A theory of quality management underlying the Deming management method" *Academy of Management Review*, 19(3): 472–509.
- *Ar I.M. and Baki B. (2011) "Antecedents and performance impacts of product versus process innovation" *European Journal of Innovation Management*, 14(2): 172–206.
- *Aragon-Correa J.A., Garcia-Morales V.J. and Cordon-Pozo E. (2007) "Leadership and organizational learning's role on innovation and performance: Lessons from Spain" *Industrial Marketing Management*, 36(3): 349–359.

- Arend R.J. and Bromiley P. (2009) "Assessing the dynamic capabilities view: Spare change, everyone?" *Strategic Organization*, 7: 75–90.
- Argote L. and Ren Y. (2012) "Transactive memory systems: A microfoundation of dynamic capabilities" *Journal of Management Studies*, 49(8): 1375–1382.
- *Artz K.W, Norman P.M., Hatfield D.E and Cardinal L.B. (2010) "A longitudinal study of the impact of R&D, patents, and product innovation on firm performance" *Journal of Product Innovation Management*, 27: 725–740.
- Atuahene-Gima K. (2005) "Resolving the capability-rigidity paradox in new product innovation" *Journal of Marketing*, 69 (October): 61–83.
- Atuahene-Gima K. and Murray J.Y. (2007) "Exploratory and exploitative learning in new product development: A social capital perspective on new technology ventures in China" *Journal of International Marketing*, 15 (2): 1–29.
- Atuahene-Gima K., Slater S.F. and Olson E.M. (2005) "The contingent value of responsive and proactive market orientations for new product program performance" *Journal of Product Innovation Management*, 22(6): 464–82.
- Audretsch D. B. and Acs Z. J. (1991) "Innovation and size at the firm level" *Southern Economic Journal*, 57(3): 739–744.
- *Baer M. and Frese M. (2003) "Innovation is not enough: Climates for initiative and psychological safety, process innovations, and firm performance" *Journal of Organizational Behavior*, 24(1): 45–68.
- Balkundi P. and Harrison D. A. (2006) "Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance" *Academy of Management Journal*, 49(1): 49–68.
- Barney J. (1991) "Firm resources and sustained competitive advantage." *Journal of Management*, 17(1): 99–120.
- Barney J. and Arikan A. (2001) "Resource-based view: Origins and implications" *The Blackwell Handbook of Strategic Management*. Blackwell: Malden, Massachusetts, US: 124–188.
- Barrales-Molina V., Martínez-López F.J. and Gázquez-Abad J.C. (2014) "Dynamic marketing capabilities: Toward an integrative framework" *International Journal of Management Reviews*, 16(4): 397–416.
- Barreto I. (2010) "Dynamic capabilities: A review of past research and an agenda for the future" *Journal of Management*, 36: 256–280.
- Baum J. A. C., Li S. X., and Usher J. M. (2000) "Making the next move: How experiential and vicarious learning shape the locations of chains' acquisitions" *Administrative Science Quarterly*, 45: 766–801.

- Begg C. B. and Mazumdar M. (1994) "Operating characteristics of a rank correlation test for publication bias" *Biometrics*, 50(4): 1088–1101.
- Benner M.J. (2009) "Dynamic or static capabilities? Process management practices and response to technological change" *Journal of Product Innovation Management*, 26: 473–486.
- Benner M.J. and Tushman M.L. (2002) "Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries". *Administrative Science Quarterly*, 47(4): 676–706.
- Benner M.J. and Tushman M.L. (2003) "Exploitation, exploration, and process management: The productivity dilemma revisited" *Academy of Management Review*, 28(2): 238–256.
- Bergman B. and Klefsjo B. (1990) "Statistical engineering for quality and productivity improvements" *European Journal of Engineering Education*, 15(3): 257–366.
- Bharadwaj A.S. (2000) "A resource-based perspective on information technology capability and firm Performance: An empirical investigation" *MIS Quarterly*, 24 (1): 169–196.
- Blau P.M. and Schoenherr R. (1971) *The Structure of Organizations*. Basic Books: New York.
- Boeker W. (1997) "Executive migration and strategic change: The effect of top manager movement on product-market entry" *Administrative Science Quarterly*, 42(2): 213–236.
- Borenstein M., Hedges L. V., Higgins J. P. T. and Rothstein H. R. (2009). *Introduction to Meta-analysis*. John Wiley and Sons: West Sussex, England.
- Bowen F.E., Rostami M. and Steel P. (2010) "Timing is everything: A meta-analysis of the relationships between organizational performance and innovation", *Journal of Business Research*, 63: 1179–1185.
- Branzei O. and Vertinsky I. (2006) "Strategic pathways to product innovation capabilities in SMEs" *Journal of Business Venturing*, 21(1): 75–105.
- Breitmayer B. J., Ayres L. and Knafl K. A. (1993) "Triangulation in qualitative research: Evaluation of completeness and confirmation purposes" *The Journal of Nursing Scholarship*, 25(3): 237–243.
- Brinckmann J., Grichnik D. and Kapsa D. (2010) "Should entrepreneurs plan or just storm the castle? A meta-analysis on contextual factors impacting the business planning-performance relationship in small firms" *Journal of Business Venturing*, 25: 24–40.
- Büschgens T., Bausch A., and Balkin D.B. (2013) "Organizational culture and innovation: A meta-analytic review" *Journal of Product Innovation Management*, 30(4): 763–781.

- Busse C. and Wallenburg C.M. (2011) "Innovation management of logistics service providers: Foundations, review, and research agenda" *International Journal of Physical Distribution and Logistics Management*, 41(2): 187–218.
- Cabral L.M.B. and Mata J. (2003) "On the evolution of the firm size distribution: Facts and theory" *The American Economic Review*, 93 (4): 1075–1090.
- Cadogan J., Sanna S., Risto S. and Kaisu P. (2002) "Market-oriented behaviour: Comparing service with product exporters" *European Journal of Marketing*, 36: 1076–1102.
- *Calantone R., Cavusgil ST. and Zhao Y. (2002) "Learning orientation, firm innovation capability, and firm performance" *Industrial Marketing Management*, 31: 515– 524.
- Calantone R., Garcia R. and Dröge C. (2003) "The effects of environmental turbulence on new product development strategy planning" *Journal of Product Innovation Management*, 20(2): 90–103.
- Calantone R., Harmancioglu N. and Dröge C. (2010) "Inconclusive innovation "Returns": A meta-analysis of research on innovation in new product development" *Journal of Product Innovation Management*, 27: 1065–1081.
- Camisón C. and Villar-López A. (2014) "Organizational innovation as an enabler of technological innovation capabilities and firm performance" *Journal of Business Research*, 67: 2891–2902.
- Camisón-Zornoza C., Lapiedra-Alcamí R., Segarra-Ciprés M. and Boronat-Navarro M. (2004) "A meta-analysis of innovation and organizational size" *Organization Studies*, 25(3): 331–361.
- Cano C.R., Carrillat F.A. and Jaramillo F. (2004) "A meta-analysis of the relationship between market orientation and business performance: Evidence from five continents" *International Journal of Research in Marketing*, 21(2): 179–200.
- Cepeda G. and Vera D. (2007) "Dynamic capabilities and operational capabilities: A knowledge management perspective" *Journal of Business Research*, 60(5): 426–437.
- Chan E. Y., Ruest A., Meade M. O. and Cook D. J. (2007) "Oral decontamination for prevention of pneumonia in mechanically ventilated adults: Systematic review and meta-analysis" *BMJ*, 334 (7599): 1–11.
- Chandy R.K. and Tellis G.J. (2000) "The incumbent's curse? Incumbency, size, and radical product innovation" *Journal of Marketing*, 64(3): 1–17.
- *Chen Y. S., Lin M. J. J. and Chang C. H. (2009) "The positive effects of relationship learning and absorptive capacity on innovation performance and competitive advantage in industrial markets" *Industrial Marketing Management*, 38(2): 152–158.
- *Chen J. S., Tsou H. T. and Huang A. Y. H. (2009) "Service delivery innovation antecedents and impact on firm performance" *Journal of Service Research*, 12(1): 36–55.

- Child J. (1973b) "Predicting and understanding organizational structure" *Administrative Science Quarterly*, 18: 168–185.
- Clegg C., Axtell C., Damodaran L., Farbey B., Hull R., Lloyd-Jones R., Nicholls J., Sell R and Tomlinson C. (1997) "Information technology: a study of performance and the role of human and organizational factors" *Ergonomics*, 40: 851–871.
- Cohen A. (1993) "Organisational commitment and turnover: A meta-analysis" *Academy of Management Journal*, 36(5): 1140–1157.
- Cohen G. (1981) "Inferential reasoning in old age" *Cognition*, 9(1): 59–72.
- Cohen J. (1977) *Statistical Power Analysis for the Behavioural Sciences*. Lawrence Erlbaum Associates, Inc.: Hillsdale, NJ, England.
- Cohen W.M. and Klepper S. (1996) "Firm size and the nature of innovation within industries: The case of process and product R&D" *The Review of Economics and Statistics*, 78(2): 232–43.
- Cohen W.M. and Levinthal D.A. (1989) "Innovation and Learning: The Two Faces of R&D" *The Economic Journal*, 99(397): 569–596.
- Coombs R. (1996) "Core competencies and the strategic management of R&D" *R&D Management*, 26(4): 345–355.
- *Coombs J. E. and Bierly P. E. (2006) "Measuring technological capability and performance" *R&D Management*, 36(4): 421–438.
- Combs J. G., Crook T. R. and Shook C. L. (2005) "The dimensionality of organizational performance and its implications for strategic management research" *Research Methodology in Strategy and Management*, 2: 259–286.
- Cooper C.L. (1998) "The changing nature of work" *Community, Work & Family*, 1(3): 313–317.
- Cooper H. (2010) *Research synthesis and meta-analysis*. Sage Publications Inc: California.
- *Craig J. and Dibrell C. (2006) "The natural environment, innovation, and firm performance: A comparative study" *Family Business Review*, 19(4): 275–288.
- Cronbach L. J. (1951) "Coefficient alpha and the internal structure of tests" *Psychometrika*, 16(3): 297–334.
- Cronbach L.J. (1971) "Test validation" *Educational Measurement*, 2: 443–507.
- Crook T. R., Ketchen D. J., Combs J. G. and Todd S. Y. (2008) "Strategic resources and performance: A meta-analysis" *Strategic Management Journal*, 29: 1141–1154.

Crook T.R., Todd S.Y., Combs J.G., Woehr D.J. and Ketchen D.J. (2011) "Does human capital matter? A meta-analysis of the relationship between human capital and firm performance" *Journal of Applied Psychology*, 96(3): 443–456.

Crosby P. (1979) *Quality Is Free*. Mentor Publishing: New York.

*Cui A.S., Griffith D.A. and Cavusgil S.T. (2005) "The Influence of competitive intensity and market dynamism on knowledge management capabilities of multinational corporation subsidiaries" *Journal of International Marketing*, 13(3): 32–53.

Daft R. L. (1983) *Organization Theory and Design*. West Publishing Co.: New York.

*Dai O. and Liu X. (2009) "Returnee entrepreneurs and firm performance in Chinese high-technology industries" *International Business Review*, 18: 373–386.

Dalton D. R., Daily C. M., Certo S. T. and Roengpitya R. (2003) "Meta-analyses of financial performance and equity: Fusion or confusion?" *Academy of Management Journal*, 46(1): 13–26.

Damanpour F. (1991) "Organizational innovation: A meta-analysis of effects of determinants and moderators" *Academy of Management Journal*, 34(3): 550–90.

Damanpour F. (1992) "Organizational size and innovation" *Organisation Studies*, 13(3): 375–402.

Damanpour F. (1996) "Organizational complexity and innovation: Developing and testing multiple contingency models" *Management Science*, 42: 693–716.

Damanpour F. and Aravind D. (2012) "Managerial innovation: Conceptions, processes, and antecedents" *Management and Organization Review*, 8(2): 423–454.

Damanpour F., Walker R.M. and Avellaneda C.N. (2009) "Combinative effects of innovation types and organizational performance: A longitudinal study of service organizations" *Journal of Management Studies*, 46(4): 650–75.

Danneels E. (2002) "The dynamics of product innovation and firm competences" *Strategic Management Journal*, 23(12): 1095–1121.

Danneels E. (2008) "Organizational antecedents of second-order competencies" *Strategic Management Journal*, 29: 519–543.

Danneels E. (2012) "Second-order competencies and Schumpeterian rents" *Strategic Entrepreneurship Journal*, 6: 42–58.

Danneels E. and Kleinschmidt E.J. (2001) "Product innovativeness from the firm's perspective: Its dimensions and their relation with project selection and performance" *Journal of Product Innovation Management*, 18(6): 357–73.

Day G. S. (2011) "Closing the marketing capabilities gap" *Journal of Marketing*, 75: 183–195.

- Davis J. P., Eisenhardt K. M. and Bingham C. B. (2009) "Optimal structure, market dynamism, and the strategy of simple rules" *Administrative Science Quarterly*, 54(3): 413–452.
- DeCarolis D.M. and Deeds D.L. (1999) "The impact of stocks and flows of organizational knowledge on firms' performance: an empirical investigation of the biotechnology industry" *Strategic Management Journal*, 20(10): 953–968.
- DeCoster J. (2009) *Meta-Analysis Notes*. www.stat-help.com/notes.html [Accessed, 27th May, 2014].
- *Deeds D. L., DeCarolis D. M. and Coombs J. E. (1998) "Firm-specific resources and wealth creation in high-technology ventures: Evidence from newly public biotechnology firms" *Entrepreneurship Theory and Practice*, 22(3): 55–73.
- Deeds D.L., DeCarolis D.M and Coombs J.E. (1999) "Dynamic capabilities and new product development in high technology ventures: An empirical analysis of new biotechnology firms". *Journal of Business Venturing*, 15: 211–229.
- Delgado-Verde M., Castro M.G. and Navas-Lopez J.E. (2011) "Organizational knowledge assets and innovation capability" *Journal of Intellectual Capital*, 12(1): 5–19.
- Deming E. (1986) *Out of the Crisis*. MIT Centre for Advanced Engineering: Cambridge, Massachusetts, US.
- Denford J.S. (2013) "Building knowledge: developing a knowledge-based dynamic capabilities typology" *Journal of Knowledge Management*, 17(2): 175–194.
- Dess G. G. and Robinson R. B. (1984) "Measuring organizational performance in the absence of objective measures: The case of the privately-held firm and conglomerate business unit" *Strategic Management Journal*, 5(3): 265–273.
- Dewar R.D. and Dutton J.E. (1986) "The adoption of radical and incremental innovations: an empirical analysis" *Management Science*, 32(11): 1422–1433.
- Di Benedetto A.C., DeSarbo W.S. and Song M. (2008) "Strategic capabilities and radical innovation: An empirical study in three countries" *IEEE Transactions on Engineering Management*, 55(3): 420–433.
- *Dibrell C., Davis P.S. and Craig J. (2008) "Fuelling innovation though information technology in SMEs" *Journal of Small Business Management*, 46(2): 203–218.
- Di Stefano G., Peteraf M. and Verona G. (2010) "Dynamic capabilities deconstructed: A bibliographic investigation into the origins, development, and future directions of the research domain" *Industrial and Corporate Change*, 19(4): 1187–1204.
- Douglas P.H. (1948) "Are there laws of production?" *The American Economic Review*, 38(1): 1–41.

- Downs Jr. G.W. and Mohr L.B. (1976) "Conceptual issues in the study of innovation" *Administrative Science Quarterly*, 21(4): 700–714.
- Drnevich P.L. and Kriauciunas A.P. (2011) "Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance" *Strategic Management Journal*, 32: 254–279.
- Drolet A. L., and Morrison D. G. (2001) "Do we really need multiple-item measures in service research?" *Journal of Service Research*, 3(3): 196–204.
- Duriau V. J., Reger R. K. and Pfarrer M. D. (2007) "A content analysis of the content analysis literature in organization studies: Research themes, data sources, and methodological refinements" *Organizational Research Methods*, 10: 5–34.
- Durmuşoğlu S.S. and Barczak G. (2011) "The use of information technology tools in new product development phases: Analysis of effects on new product innovativeness, quality, and market performance" *Industrial Marketing Management*, 40: 321–330.
- Duval S. and Tweedie R. (2000a) "A nonparametric "trim and fill" method of accounting for publication bias in meta-analysis" *Journal of the American Statistical Association*, 95(449): 89–98.
- Duval S. and Tweedie R. (2000b) "Trim and fill: A simple funnel-plot based method of testing and adjusting for publication bias in meta-analysis" *Biometrics*, 56(2): 455–463.
- Egger M., Smith G. D., Schneider M. and Minder C. (1997) "Bias in meta-analysis detected by a simple, graphical test" *BMJ*, 315 (7109): 629–634.
- Eisenhardt K.M. and Martin J.A. (2000) "Dynamic capabilities: What are they?" *Strategic Management Journal*, 21: 1105–1121.
- *Eisingerich A. B., Rubera G. and Seifert M. (2009) "Managing service innovation and interorganizational relationships for firm performance to commit or diversify?" *Journal of Service Research*, 11(4): 344–356.
- *Ettlie J.E. and Pavlou P.A. (2006) "Technology-based new product development partnerships" *Decision Sciences*, 37(2): 117–147.
- Ettlie J.E. and Rubenstein A.H. (1987) "Firm size and product innovation" *Journal of Product Innovation Management*, 4: 89–108.
- Evanschitzky H., Eisend M., Calantone R.J. and Jiang Y. (2012) "Success factors of product innovation: An updated meta-analysis" *Journal of Product Innovation Management*, 29: 21–37.
- Felin T., Foss N. J., Heimeriks K. H. and Madsen T. L. (2012) "Microfoundations of routines and capabilities: Individuals, processes, and structure" *Journal of Management Studies*, 49(8): 1351–1374.

- Flor M. and Oltra M.J. (2005) "The influence of firms' technological capabilities on export performance in supplier dominated industries: The case of ceramic tiles firms" *R&D Management*, 35(3): 333–347.
- Forza C. (2002) "Survey research in operations management: A process-based perspective" *International Journal of Operations & Production Management*, 22(2): 152–171.
- Gaba V., Pan Y. and Ungson G. R. (2002) "Timing of entry in international market: An empirical study of US Fortune 500 firms in China" *Journal of International Business Studies*: 39–55.
- Garcia R. and Calantone R. (2002) "A critical look at technological innovation typology and innovativeness terminology: A literature review" *Journal of Product Innovation Management* 19(2): 110–32.
- *Garcia-Morales V. J., Lloréns-Montes F. J. and Verdú-Jover A. J. (2007) "Influence of personal mastery on organizational performance through organizational learning and innovation in large firms and SMEs" *Technovation*, 27(9): 547–568.
- *Garg V. K., Walters B. A. and Priem R. L. (2003) "Chief executive scanning emphases, environmental dynamism, and manufacturing firm performance" *Strategic Management Journal*, 24(8): 725–744.
- Garvin D.A. (1995) "Leveraging processes for strategic advantage" *Harvard Business Review* 73(5): 77–90.
- Gatignon H. and Xuereb J.M. (1997) "Strategic orientation of the firm and new product performance" *Journal of Marketing Research*, 34: 77–90.
- Geyskens I., Krishnan R., Steenkamp J.E.M. and Cunha P.V. (2009) "A review and evaluation of meta-analysis practices in management research" *Journal of Management*, 35(2): 393–419.
- Geyskens I., Steenkamp J. B. E. and Kumar N. (1999) "A meta-analysis of satisfaction in marketing channel relationships" *Journal of Marketing Research*, 36: 223–238.
- Ghemawat P. and Costa J. (1993) "The organizational tension between static and dynamic efficiency" *Strategic Management Journal*, 14: 59–73.
- Glass G.V. (1976) "Primary, secondary, and meta-analysis of research" *Educational Researcher*, 3–8.
- Gooding R. Z. and Wagner III J. A. (1985) "A meta-analytic review of the relationship between size and performance: The productivity and efficiency of organizations and their subunits" *Administrative Science Quarterly*, 30(4): 462–481.
- *Gopalakrishnan S. (2000) "Unravelling the links between dimensions of innovation and organizational performance" *The Journal of High Technology Management Research*, 11(1): 137–153.

- Grant R.M. (1996a) "Prospering in dynamically-competitive environments: organizational capability as knowledge integration" *Organization Science*, 7(4): 375–87.
- Grant R.M. (1996b) "Toward a knowledge-based theory of the firm" *Strategic Management Journal*, 17(Special Issue):109–122.
- *Grawe S.J., Chen H. and Daugherty P.J. (2009) "The relationship between strategic orientation, service innovation, and performance" *International Journal of Physical Distribution and Logistics Management*, 39 (4): 282–300.
- Green S.G, Gavin M.B. and Aiman-Smith L. (1995) "Assessing a multidimensional measure of radical technological innovation" *IEEE Transactions on Engineering Management*, 42(3): 203–15.
- Greenley G. (1995) "Market orientation and company performance: Empirical evidence from UK companies" *British Journal of Management*, 6 (December): 1–13.
- Grewal R. and Tansuhaj (2001) "Building organizational capabilities for managing economic crisis: The role of market orientation and strategic flexibility" *Journal of Marketing*, 65: 67–80.
- Grinstein A. (2008a) "The relationships between market orientation and alternative strategic orientations: A meta-analysis" *European Journal of Marketing*, 42(1/2):115–134.
- Grinstein A. (2008b) "The effect of market orientation and its components on innovation consequences: A meta-analysis" *Journal of Academy of Marketing Science*, 36: 166–173.
- *Guan J. and Ma N. (2003) "Innovative capability and export performance of Chinese firms" *Technovation*, 23(9): 737–747.
- Guan J.C., Yam R.C.M, Tang E.P.Y and Lau A.K.W (2009) "Innovation strategy and performance during economic transition: Evidences in Beijing, China" *Research Policy*, 23: 802–812.
- Gujarati D. N. (2006) *Essentials of Econometrics* (3rd ed.). McGraw-Hill/Irwin: Boston, Massachusetts, US.
- Gulliksen H. (1986) "The increasing importance of mathematics in psychological research (Part 3)" *The Score*, 9: 1–5.
- Guzzo R.A., Jackson S.E. and Katzell R.A. (1987) "Meta-analysis analysis" *Research in Organizational Behaviour*, 9, L.L. Cummings and B.M. Staw (eds), Greenwich CT: Jai Press: 407–442.
- Hackman J. R. and Wageman R. (1995) "Total quality management: Empirical, conceptual, and practical issues" *Administrative Science Quarterly*, 40: 309–342.
- Hage J. (1980). *Theories of Organisations*. Wiley: New York.

- Hage J. and Aiken M. (1970) *Social Change in Complex Organisations*. Random House: New York.
- Halcomb E. J. and Andrew S. (2005) "Triangulation as a method for contemporary nursing research" *Nurse Researcher*, 13(2): 71–82.
- Hall J., Tickle-Degnen L., Rosenthal R.R. and Mosteller F. (1993) "Hypotheses and problems in research synthesis" In L.V. Hedges and H. Cooper (eds.) *Handbook of Research Synthesis*, Russell Sage: New York: 17–28.
- Han J.K, Kim N. and Srivastava R.K. (1998) "Market orientation and organizational performance: Is innovation a missing link?" *Journal of Marketing*, 62(4): 30–45.
- Harrison D.A., Newman D.A. and Roth P.L. (2006) "How important are job attitudes? Meta-analytic comparisons of integrative behavioural outcomes and time sequences" *Academy of Management Journal*, 49(2): 305–25.
- Harry M. and Schroeder R. (2000) *Six Sigma: The Breakthrough Management Strategy Revolutionizing the World's Top Corporations*. Currency: New York.
- Hauser J., Tellis G. J. and Griffin A. (2006) "Research on innovation: A review and agenda for marketing science" *Marketing Science*, 25(6): 687–717.
- Hedges L.V. and Olkin I. (1985) *Statistical Methods for Meta-analysis*. Academic Press, Inc.: Orlando, FL, US.
- Hedges L. V. and Vevea J. L. (1998) "Fixed-and random-effects models in meta-analysis" *Psychological Methods*, 3(4): 486–504.
- *Heeley M. B., Matusik S. F. and Jain N. (2007) "Innovation, appropriability, and the underpricing of initial public offerings" *Academy of Management Journal*, 50(1): 209–225.
- Helfat C.E., Finkelstein S., Mitchell W., Peteraf M. A., Singh H., Teece D.J. and Winter S. G. (2007) *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Blackwell: London.
- Helfat C.E. and Peteraf M. A. (2003) "The dynamic resource-based view: Capability lifecycles" *Strategic Management Journal*, 24(10): 997–1010.
- Helfat C.E. and Peteraf M.A. (2009) "Understanding dynamic capabilities: Progress along a developmental path" *Strategic Organization*, 7(1): 91–10.
- Helfat C.E. and Peteraf M.A. (2014) "Managerial cognitive capabilities and the microfoundations of dynamic capabilities" *Strategic Management Journal*, doi: 10.1002/smj.2247
- Helfat C.E. and Winter S.G. (2011) "Untangling dynamic and operational capabilities: Strategy for the (n)ever-changing world" *Strategic Management Journal*, 32(11): 1243–1250.

- Henard D. H. and Szymanski D.M. (2001) "Why some new products are more successful than others" *Journal of Marketing Research*, 38: 362–75.
- Heugens P.P.M.A.R. and Lander M. (2009) "Structure! agency! (and other quarrels): A meta-analysis of institutional theories of organization" *Academy of Management Journal*, 52(1): 61–85.
- *Heunks F. J. (1998) "Innovation, creativity and success" *Small Business Economics*, 10(3): 263–272.
- Hitt M.A., Hoskisson R.E. and Kim H. (1997) "International diversification: Effects on innovation and firm performance in product-diversified firms" *Academy of Management Journal*, 40: 767–98.
- Hogan S. J., Soutar G. N., McColl-Kennedy J. R. and Sweeney J. C. (2011) "Reconceptualizing professional service firm innovation capability: Scale development". *Industrial Marketing Management*, 40(8): 1264–1273.
- Holdaway E. A. and Blowers T. A. (1971) "Administrative ratios and organization size: A longitudinal examination" *American Sociological Review*, 36(2): 278–286.
- Hooley G.J., Greenly G.E., Cadogan J.W. and Fahy J. (2005) "The performance impact of marketing resources" *Journal of Business Research*, 58(1):18–27.
- Howell J.M., Shea C.M. and Higgins C.A. (2005) "Champions of product innovations: Defining, developing, and validating a measure of champion behaviour" *Journal of Business Venturing*, 20: 641–661.
- Huang H.C. (2011) "Technological innovation capability creation potential of open innovation: A cross-level analysis in the biotechnology industry" *Technology Analysis & Strategic Management*, 23(1): 49–63.
- Huber P.J. (1980) *Robust Statistics*. Wiley: New York.
- *Hult G.T.M, Hurley R.F. and Knight G.A. (2004) "Innovativeness: Its antecedents and impact on business performance" *Industrial Marketing Management*, 33: 429–438.
- Hunter J. E. and Hirsch H. R. (1987) "Applications of meta-analysis", in Cooper C. L. and Robertson I. T. (Eds) *International Review of Industrial and Organizational Psychology*, John Wiley and Sons Limited, Chichester: 192–224.
- Hunter J. E. and Schmidt F. L. (1990) *Methods of Meta-analysis: Correcting Error and Bias in Research Findings*. Sage Publications Inc.: Newbury Park, CA.
- Hunter J. E. and Schmidt F. L. (2004) *Methods of Meta-analysis: Correcting Error and Bias in Research Findings* (2nd ed). Sage Publications Inc.: Newbury Park, CA.
- Hunter J. E., Schmidt F. L. and Jackson G. B. (1982) *Meta-analysis: Cumulating Research Findings Across Studies* (4th ed). Sage Publications Inc.: Newbury Park, CA.
- Hurley R.F. and Hult G.T.M. (1998) "Innovation, market orientation, and organizational learning: An integration and empirical examination" *Journal of Marketing*, 62: 42–54.

- Indik B. P. (1964) "The relationship between organization size and supervision ratio" *Administrative Science Quarterly*, 9(3): 301–312.
- Jacoby J. (1978) "Consumer research: A state of the art review" *The Journal of Marketing*, 42(2): 87–96.
- *Jansen J. J., Van Den Bosch F. A. and Volberda H. W. (2006) "Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators" *Management Science*, 52(11): 1661–1674.
- Jaworski B. J. and Kohli A. K. (1993) "Market orientation: Antecedents and consequences" *The Journal of Marketing*, 57(3): 53–70.
- Jervis P. (1975) "Innovation and technology transfer—the roles and characteristics of individuals" *IEEE Transactions on Engineering Management*, 1: 19–27.
- *Jiménez-Jiménez D. and Sanz-Valle R. (2011) "Innovation, organizational learning, and performance" *Journal of Business Research*, 64: 408–417.
- Joshi A. and Roh H. (2009) "The role of context in work team diversity research: A meta-analytic review" *Academy of Management Journal*, 52 (3): 599–627.
- *Kalafsky R. V. and MacPherson A. D. (2002) "The competitive characteristics of US manufacturers in the machine tool industry" *Small Business Economics*, 19(4): 355–369.
- Kaplinski R. and Paulino A.S. (2005) "Innovation and competitiveness: Trends in unit prices in global trade" *Oxford Development Studies*, 33: 333–355.
- *Katila R. and Ahuja G. (2002) "Something old, something new: A longitudinal study of search behavior and new product introduction" *Academy of Management Journal*, 45(6): 1183–1194.
- Kellermanns F.W., Walter J., Floyd F.W., Lechner C. and Shaw J.C. (2011) "To agree or not to agree? A meta-analytical review of strategic consensus and organizational performance" *Journal of Business Research*, 64: 126–133.
- Ketchen D. J., Hult G. T. M. and Slater S. F. (2007) "Toward greater understanding of market orientation and the resource-based view" *Strategic Management Journal*, 28(9): 961–964.
- *Kim D., Basu C., Naidu G. M. and Cavusgil E. (2011) "The innovativeness of born-globals and customer orientation: Learning from Indian born-globals" *Journal of Business Research*, 64(8): 879–886.
- Kim W.C. and Maubourgne R. (2005) *Blue Ocean Strategy*. Harvard Business School Press: Boston, MA.
- Kimberly J.R. (1976) "Organizational size and the structuralist perspective; A review, critique, and proposal" *Administrative Science Quarterly*, 21: 571–597.

- Kimberly J.R. and Evanisko M.J. (1981) "Organizational innovation: The influence of individual organizational and contextual factors on hospital adoption of technological and administrative innovation" *Academy of Management Journal*, 24(4): 689–713.
- Kirca A. H., Hult G. T. M., Roth K., Cavusgil S. T., Perry M.Z., Akdeniz M. B., Deligonul S. Z., Mena J. A., Politt W. A., Hoppner J. J., Miller J. C. and White R. C. (2011) "Firm specific assets, multinationality, and financial performance: A meta-analytic review and theoretical integration" *Academy of Management Journal*, 54(1): 47–72.
- Kirca A. H., Satish J. and William O. B. (2005) "Market orientation: A meta-analytic review and assessment of its antecedents and impact on performance" *Journal of Marketing*, 69: 24–41.
- Kohli A. and Jaworski B. (1990) "Market orientation: The construct, research propositions and managerial implications" *Journal of Marketing*, 54: 1–18.
- Kohn C. A. and Jacoby J. (1973) "Operationally defining the consumer innovator" *Proceedings of the Annual Convention of the American Psychological Association*. (American Psychological Association): 28–42.
- Kozlenkova I.V., Samaha S.A. and Palmatier R.W. (2013) "Resource-based theory in marketing" *Journal of Academy of Marketing Science*, 42(1): 1–21.
- Krasnikov A. and Jayachandran S. (2008) "The relative impact of marketing, research and development, and operation capabilities on firm performance" *Journal of Marketing*, 72: 1–11.
- *Kuckertz A., Kohtamäki M. and Droege gen. Körber C. (2010) "The fast eat the slow—the impact of strategy and innovation timing on the success of technology-oriented ventures" *International Journal of Technology Management*, 52(1/2): 175–188.
- Laforet S. (2008) "Size, strategic, and market orientation affects on innovation" *Journal of Business Research*, 61: 753–764.
- Lavía C., Otero B., Olazaran M. and Albizu E. (2011) "Innovación y territorio. Una encuesta a pequeñas y medianas empresas industriales" *Revista Internacional de Sociología*, 69(2): 461–486.
- Lawson B. and Samson D. (2001) "Developing innovation capability in organizations: A dynamic capabilities approach" *International Journal of Innovation Management*, 5(3): 377–400.
- *Lawson B., Samson D. and Roden S. (2012) "Appropriating the value from innovation: Inimitability and the effectiveness of isolating mechanisms" *R&D Management*, 42(5): 420–434.
- *Lee C., Lee K. and Pennings J. M. (2001) "Internal capabilities, external networks, and performance: A study on technology-based ventures" *Strategic Management Journal*, 22(6-7): 615–640.

- Lefebvre E., Lefebvre L. and Bourgault M. (1998) "R&D-related capabilities as determinants of export performance" *Small Business Economics*, 10: 365–377.
- Lengnick-Hall C.A. and Wolff J.A. (1999) "Similarities and contradictions in the core logic of three strategy research streams" *Strategic Management Journal*, 20 (12): 1109–1132.
- Leuschner R., Charvet F. and Rogers D.S. (2013) "A meta-analysis of logistics customer service" *Journal of Supply Chain Management*, 49(1): 47–63.
- Levinthal D. (2000) "Organizational capabilities in complex worlds" In Dosi G., Nelson R.R. and Winter S.G. (Eds) *The Nature and Dynamics of Organizational Capabilities*, Oxford University Press: New York. 363–379.
- Levinthal D. and March J. G. (1993) "The myopia of learning" *Strategic Management Journal*, 14: 95–112.
- *Li H. and Atuahene-Gima K. (2001) "Product innovation strategy and the performance of new technology ventures in China" *Academy of Management Journal*, 44(6): 1123–1134.
- Li H. and Atuahene-Gima K. (2002) "The adoption of agency business activity, product innovation, and performance in Chinese technology ventures" *Strategic Management Journal*, 23(6): 469–490.
- Li A. and Cropanzano R. (2009) "Do East Asians respond more/less strongly to organizational justice than North American? A meta-analysis" *Journal of Management Studies*, 46(5): 787–805.
- Li D. and Liu J. (2014) "Dynamic capabilities, environmental dynamism, and competitive advantage: Evidence from China" *Journal of Business Research*, 67: 2793–2799.
- Liang T.P., You J.J. and Liu C.C (2010) "A resource-based perspective on information technology and firm performance: A meta-analysis" *Industrial Management & Data Systems*, 110 (8): 1138–1158.
- Lichtenthaler U. (2009) "Outbound open innovation and its effect on firm performance: Examining environmental influences" *R&D Management*, 39 (4): 317–330.
- Lichtenthaler U. and Muethel M. (2012) "The impact of family involvement on dynamic innovation capabilities: Evidence from German manufacturing firms" *Entrepreneurship Theory and Practice*, 36(6): 1235–1253.
- *Lin M.J and Chen C. (2008) "Integration and knowledge sharing: Transforming to long-term competitive advantage" *International Journal of Organisational Analysis*, 16(1/2): 83–108.
- Lipsey M. W. and Wilson D. B. (2001) *Practical Meta-analysis*. Sage Publications, Inc.: Thousand Oaks, California.
- Liu T.C. and Chen Y.J. (2015) "Strategy orientation, product innovativeness, and new product performance" *Journal of Management & Organization*, 21: 2–16.

- Liu H., Ding X., Guo H. and Luo J. (2014) "How does slack affect product innovation in high-tech Chinese firms: The contingent value of entrepreneurial orientation" *Asia Pacific Journal of Management*, 31: 47–68.
- *Löf H. and Heshmati A. (2006) "On the relationship between innovation and performance: A sensitivity analysis" *Economics of Innovation and New Technology*, 15(4-5): 317–344.
- López S. V. (2005) "Competitive advantage and strategy formulation: The key role of dynamic capabilities" *Management decision*, 43(5): 661–669.
- Lubatkin M.H., Simsek Z., Ling Y. and Veiga J.F. (2006) "Ambidexterity and performance in small to medium sized firms: The pivotal role of top management behavioural integration" *Journal of Management*, 32(5): 646–672.
- *Luo X., Sivakumar K. and Liu S. S. (2005) "Globalization, marketing resources, and performance: Evidence from China" *Journal of the Academy of Marketing Science*, 33(1): 50–65.
- MacCallum R.C. and Austin J.T. (2000) "Applications of structural equation modeling in psychological research" *Annual Review of Psychology*, 51: 201–226.
- MacKenzie S.B. (2003) "The dangers of poor construct conceptualisation" *Journal of the Academy of Marketing Science*, 31(3): 323–326.
- MacKenzie S.B., Podsakoff P.M. and Jarvis C.B. (2005) "The problem of measurement model misspecification in behavioural and organizational research and some recommended solutions" *Journal of Applied Psychology*, 90(4): 710–730.
- Makadok R. (2001) "Toward a synthesis of the resource-based and dynamic-capability views of rent creation" *Strategic Management Journal*, 22(5): 387–401.
- Malhotra N.K. (2014) *Basic Marketing Research* (4th ed.). Pearson Education: Essex, UK.
- March J. G. (1991) "Exploration and exploitation in organizational learning" *Organizational Science*, 2 (1): 71–87.
- Marsh S.J. and Stock G.N. (2003) "Building dynamic capabilities in new product development through inter-temporal integration" *Journal of Product Innovation Management*, 20(2): 136–148.
- McDaniel M. A., Rothstein H. R. and Whetzel D. L. (2006) "Publication bias: A case study of four test vendors" *Personnel Psychology*, 59: 927–953.
- McEvoy G. M. and Cascio W. F. (1987) "Do good or poor performers leave? A meta-analysis of the relationship between performance and turnover" *Academy of Management Journal*, 30(4): 744–762.

- Menguc B. and Auh S. (2006) "Creating a firm-level dynamic capability through capitalizing on market orientation and innovativeness" *Journal of the Academy of Marketing Science*, 34(1): 63–73.
- Merrilees B., Rundle-Thiele S. and Lye A. (2011) "Marketing capabilities: Antecedents and implications for B2B SME performance" *Industrial Marketing Management*, 40: 368–375.
- Miles M.P., Covin J.G. and Heeley M.B. (2000) "The relationship between environmental dynamism and small firm structure, strategy and performance" *Journal of Marketing Theory and Practice*, 8 (2): 63–74.
- Miller D. and Friesen P. H. (1983) "Strategy-making and environment: The third link" *Strategic Management Journal*, 4(3): 221–235.
- Miller C.C., Glick W.H., Wang Y-D and Huber G.P. (1991) "Understanding technology-structure relationships: Theory development and meta-analytic theory testing" *Academy of Management Journal*, 34(2): 370–399.
- Mills P. K. and Margulies N. (1980) "Toward a core typology of service organizations" *Academy of Management Review*, 5(2): 255–266.
- Mitchell B. (1989) *Geography and Resource Analysis* (2nd ed.). Longman: Essex, UK.
- *Mithas S., Ramasubbu N. and Sambamurthy V. (2011) "How information management capability influences firm performance" *MIS Quarterly*, 35(1): 237–256.
- Molina-Castillo F. J. and Munuera-Aleman J. L. (2009) "The joint impact of quality and innovativeness on short-term new product performance" *Industrial Marketing Management*, 38(8): 984–993.
- Montoya-Weiss M.M. and Calantone R. (1994) "Determinants of new product performance: A review and meta-analysis" *Journal of Product Innovation Management*, 11(5): 397–417.
- Morgan N. A., Vorhies D. W. and Mason C. H. (2009) "Market orientation, marketing capabilities, and firm performance" *Strategic Management Journal*, 30(8): 909–920.
- Neely A. and Hii J. (1998) *Innovation and business performance: A literature Review*. The Judge Institute of Management Studies, University of Cambridge Press: Cambridge, UK.
- Nelson R.R. (1993) *National Innovation Systems: A Comparative Analysis*. University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership, Historical Research Reference in Entrepreneurship: Illinois, US.
- Newbert S. L. (2007) "Empirical research on the resource-based view of the firm: An assessment and suggestions for future research" *Strategic Management Journal*, 28(2):121–146.

- Nohria N. and Gulati R. (1996) "Is slack good or bad for innovation?" *Academy of Management Journal*, 39(5): 1245–1264.
- Noor M.N.M and Pitt M. (2009) "A critical review on innovation in facilities management service delivery" *Facilities*, 27(5/6): 211–228.
- Nunnally J.C. (1967) *Psychometric Theory*. McGraw-Hill: New York.
- Nunnally J.C. and Bernstein I.A. (1994) *Psychometric Theory* (3rd ed.). McGraw-Hill: New York.
- O'Cass A. and Ngo L.V. (2012) "Creating superior customer value for B2B firms through supplier firm capabilities" *Industrial Marketing Management*, 41: 125–135.
- *O'Cass A. and Sok P. (2013a) "Exploring innovation driven value creation in B2B service firms: The roles of the manager, employees, and customers in value creation" *Journal of Business Research*, 66(8): 1074–1084.
- *O'Cass A. and Sok P. (2013b) "The role of intellectual resources, product innovation capability, reputational resources and marketing capability combinations in small and medium-sized enterprise growth" *International Small Business Journal*, 0(0): 1–25.
- OECD (1992) *Proposed Guidelines for Collecting and Interpreting Technological Innovation Data*. OSLO Manual, OECD-Eurostat: Paris.
- OECD (1997) *Proposed Guidelines for Collecting and Interpreting Technological Innovation Data* (2nd ed.) OSLO Manual, OECD-Eurostat: Paris.
- Oke A., Burke G. and Myers A. (2007) "Innovation types and performance in growing UK SMEs" *International Journal of Operations & Production Management*, 27(7): 735–753.
- O'Reilly III C.A. and Tushman M. L. (2008) "Ambidexterity as a dynamic capability: Resolving the innovator's dilemma" *Research in Organizational Behavior*, 28: 185–206.
- Orwin R. G. (1983) "A fail-safe N for effect size in meta-analysis" *Journal of educational statistics*, 8(2): 157–159.
- Oshri I., Pan S.L. and Newell S. (2005) "Trade-offs between knowledge exploitation and exploration activities" *Knowledge Management Research & Practice*, (3): 10–23.
- *Panayides P. (2006) "Enhancing innovation capability through relationship management and implications for performance" *European Journal of Innovation Management*, 9(4): 466–483.
- Pavitt K., Robson M. and Townsend J. (1987) "The size distribution of innovating firms in the UK 1945–1983" *Journal of Industrial Economics*, 35: 297–316.
- *Penner-Hahn J. and Shaver J.M. (2005) "Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms" *Strategic Management Journal*, 26: 121–140.

- Persaud A. (2005) "Enhancing synergistic innovative capability in multinational corporations: An empirical investigation" *Journal of Product Innovation Management*, 22: 412–429.
- Peter P.J. (1981) "Construct validity: A review of basic issues and marketing practices" *Journal of Marketing Research*, 18: 133–145.
- Peteraf M., Di Stefano G. and Verona G. (2013) "The elephant in the room of dynamic capabilities: Bringing two diverging conversations together" *Strategic Management Journal*, 34: 1389–1410.
- Phillips J.M. (1998) "Effects of realistic job previews on multiple organizational outcomes: A meta-analysis" *Academy of Management Journal*, 41(6): 673–690.
- Poole M.S. and Van de Ven A.H. (1989) "Toward a general theory of innovation processes" In Van de Ven A. H., Angle H. L. and Poole M. S. (Eds.), *Research on the Management of Innovation: The Minnesota Studies*. Harper & Row: New York: 637–662.
- Porter M.E. (1985) *Competitive Advantage*. Free Press: New York.
- Porter M.E. (1990) "The competitive advantage of nations" *Harvard Business Review*, 68: 73–93.
- Powell T.C. and Dent-Micallef A. (1997) "Information technology as competitive advantage: The role of human, business, and technology resources" *Strategic Management Journal*, 18(5): 375–405.
- Priem R. L. and Butler J. E. (2001) "Is the resource-based "view" a useful perspective for strategic management research?" *Academy of Management Review*, 26(1): 22–40.
- Product Development and Management Association (PDMA) (2004) *The PDMA glossary for new product development*. <http://www.pdma.org/p/cm/ld/fid=27>. [Assessed 14 May, 2012].
- Protopogrou A., Caloghirou Y. and Lioukas S. (2012) "Dynamic capabilities and their indirect impact on firm performance" *Industrial and Corporate Change*, 21(3): 615–647.
- Raisch S. and Birkinshaw J. (2008) "Organizational ambidexterity: Antecedents, outcomes, and moderators" *Journal of Management*, 34(3): 375–409.
- Ravichandran T. and Rai A. (1999) "Total quality management in information systems development: Key constructs and relationships" *Journal of Management Information Systems*, 16(3): 119–155.
- Read S., Song M. and Smit W. (2009) "A meta-analytic review of effectuation and venture performance" *Journal of Business Venturing*, 24(6): 573–587.
- *Rhodes J., Hung R., Lok P., Lien B. Y. H. and Wu C. M. (2008) "Factors influencing organizational knowledge transfer: Implication for corporate performance" *Journal of Knowledge Management*, 12(3): 84–100.

- *Richard O. C., Barnett T., Dwyer S. and Chadwick K. (2004) "Cultural diversity in management, firm performance, and the moderating role of entrepreneurial orientation dimensions" *Academy of Management Journal*, 47(2): 255–266.
- *Richard O.C., McMillan A., Chadwick K. and Dwyer S. (2003) "Employing an innovation strategy in racially diverse workforces effects on firm performance" *Group & Organization Management*, 28(1): 107–126.
- Rogers M. (2004) "Networks, firm size and innovation" *Small Business Economics*, 22: 141–153.
- Rosenbusch N., Brinckmann J. and Bausch A. (2011) "Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs" *Journal of Business Venturing*, 26: 441–457.
- Rosenthal R. (1979) "The file drawer problem and the tolerance for null results" *Psychological Bulletin*, 86 (3): 638–641.
- Rosenthal R. (1995) "Writing meta-analytic reviews" *Psychological Bulletin*, 118(3): 183–192.
- Rubera G. and Kirca A.H. (2012) "Firm innovativeness and its performance outcomes: A meta-analytic review and theoretical integration", *Journal of Marketing*, 76: 130–147.
- Rust R. T., Ambler T., Carpenter G. S., Kumar V. and Srivastava R. K. (2004) "Measuring marketing productivity: Current knowledge and future directions" *Journal of Marketing*, 68(4): 76-89.
- Sagie A. and Koslowsky M. (1993) "Detecting moderators with meta-analysis: An evaluation and comparison of techniques" *Personnel Psychology*, 46 (3): 629–640.
- *Salomo S., Talke K. and Strecker N. (2008) "Innovation field orientation and its effect on innovativeness and firm performance" *Journal of Product Innovation Management*, 25: 560–576.
- Salunke S., Weerawardena J. and McColl-Kennedy J. R. (2011) "Towards a model of dynamic capabilities in innovation-based competitive strategy: Insights from project-oriented service firms" *Industrial Marketing Management*, 40(8): 1251–1263.
- Santos B.D. and Sussman L. (2000) "Improving the return on IT investment: The productivity paradox" *International Journal of Information Management*, 20 (6): 429–440.
- Särndal C. E., Swensson B. and Wretman J. (1992) *Model Assisted Survey Sampling*. Springer-Verlag: New York.
- Sarooghi, H., Libaers D. and Burkemper A. (2015) "Examining the relationship between creativity and innovation: A meta-analysis of organizational, cultural, and environmental factors" *Journal of Business Venturing*, <http://dx.doi.org/10.1016/j.jbusvent.2014.12.003>.
- Scherer F. M. (1965) "Firm size, market structure, opportunity, and the output of patented inventions" *The American Economic Review*, 55 (5): 1097–1125.

- Scherer F. M. (1982) "Inter-industry technology flows in the United States" *Research Policy*, 11(4): 227–245.
- Scherer F.M. and Ross D. (1990) *Industrial Market Structure and Economic Performance*. Houghton Mifflin: Boston, Massachusetts, US.
- *Schilke O. (2014) "On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism" *Strategic Management Journal*, 35: 179–203.
- Schmidt F.L. and Hunter J.E. (1996) "Measurement error in psychological research: Lessons from 26 research scenarios" *Psychological Methods*, 1(2): 199–223.
- *Schoenecker T. and Swanson L. (2002) "Indicators of firm technological capability: Validity and performance implications" *IEEE Transactions on Engineering Management*, 49(1): 36–44.
- Schreyoegg G. and Kliesch-Eberl M. (2007) "How dynamic can organizational capabilities be? Towards a dual process model of capability dynamization" *Strategic Management Journal*, 28: 913–933.
- Schumpeter J.A. (1934) *The Theory of Economic Development*. Harvard University Press: Cambridge, Massachusetts, US.
- Schumpeter J.A. (1942) *Capitalism, Socialism and Democracy*. Harper and Row: New York.
- Schumpeter J.A. (1950) *Capitalism, Socialism and Democracy* (3rd ed.). Harper and Row: New York.
- Shephard R. W. and Färe R. (1974) *The Law of Diminishing Returns*. Springer Heidelberg: Berlin.
- Shih F. J. (1998) "Triangulation in nursing research: Issues of conceptual clarity and purpose" *Journal of Advanced Nursing*, 28(3): 631–641.
- Siguaw J.A., Simpson P.M. and Enz C.A. (2006) "Conceptualizing innovation orientation: A framework for study and integration of innovation research" *Journal of Product Innovation Management*, 23: 556–574.
- *Sirén C.A., Kohtamäki M. and Kuckertz A. (2012) "Exploration and exploitation strategies, profit performance, and the mediating role of strategic learning: Escaping the exploitation trap" *Strategic Entrepreneurship Journal*, 6: 18–41.
- Simon D.G., Hitt M.A., Arregle J-L. and Campbell J.T. (2010) "The dynamic interplay of capability strengths and weaknesses: Investigating the bases of temporary competitive advantage" *Strategic Management Journal*, 31(13): 1386–1409.

- Sivasubramaniam N., Liebowitz S.J. and Lackman C.L. (2012) "Determinants of new product development team performance: A meta-analytic review" *Journal of Product Innovation Management* 29(5): 803–820.
- Slater S.F., Mohr J.J. and Sengupta S. (2014) "Radical product innovation capability: Literature review, synthesis, and illustrative research propositions" *Journal of Product Innovation Management*, 31(3): 552–566.
- Sok P. and O'Cass A. (2011) "Achieving superior innovation-based performance outcomes in SMEs through innovation resource-capability complementarity" *Industrial Marketing Management*, 40(8): 1285–1293.
- Song M., Droge C., Hanvanich S. and Calantone R. (2005) "Marketing and technology resource complementarity: An analysis of their interaction effect in two environmental contexts" *Strategic Management Journal*, 26(3): 259–276.
- Song M. and Montoya-Weiss M. M. (2001) "The effect of perceived technological uncertainty on Japanese new product development" *Academy of Management Journal*, 44(1): 61–80.
- Spillman W.J. and Lang E. (1924) *The Law of Diminishing Returns*. World Book Co.: New York.
- Stam W., Arzlanian S. and Elfring T. (2014) "Social capital of entrepreneurs and small firm performance: A meta-analysis of contextual and methodological moderators" *Journal of Business Venturing*, 29(1): 152–173.
- Stratopoulos T. and Dehning B. (2000) "Does successful investment in information technology solve the productivity paradox?" *Information & Management*, 38: 103–117.
- *Tatikonda M. V. and Montoya-Weiss M. M. (2001) "Integrating operations and marketing perspectives of product innovation: The influence of organizational process factors and capabilities on development performance" *Management Science*, 47(1): 151–172.
- Teece D.J. and Pisano G. (1994) "The dynamic capabilities of firms: An introduction" *Industrial and Corporate Change*, 3(3): 537–556.
- Teece D.J., Pisano G. and Shuen A. (1997) "Dynamic capabilities and strategic management" *Strategic Management Journal*, 18(7): 509–533.
- Teece D.J. (2007) "Explicating dynamic capabilities: The nature and micro foundations of (sustainable) enterprise performance" *Strategic Management Journal*, 28(13): 1319–1350.
- Teece D.J. (2009) *Dynamic Capabilities and Strategic Management: Organizing for Innovation and Growth*. Oxford University Press: Oxford, UK.
- The International Monetary Fund (2012) *Selected Online IMF Data Sources*. www.imf.org/external/np/ds/matrix.htm. [Accessed, 29th April, 2013].

- The World Bank (2011) *Science and Technology Databases*. <http://data.worldbank.org/topic/science-and-technology>. [Accessed, 30th April, 2013].
- Thorndike R. L. and Hagen E. (1977) *Measurement and Evaluation in Psychology and Education* (4th ed). John Wiley & Sons: New York.
- *Thornhill S. (2006) "Knowledge, innovation and firm performance in high- and low-technology regimes" *Journal of Business Venturing*, 21: 687–703.
- Tidd J. (1995) "Development of novel products through intraorganizational and interorganizational networks" *Journal of Product Innovation Management*, 12(4): 307–322.
- Tidd J. (1997) "Complexity, networks & learning: Integrative themes for research on innovation management" *International Journal of Innovation Management*, 1(01): 1–21.
- Tidd J. (2001) "Innovation management in context: Environment, organization and performance" *International Journal of Management Reviews*, 3(3): 169–183.
- Trott P. and Hoecht A. (2004) "Enterprise Resource Planning and the Price of Efficiency: The Trade Off Between Business Efficiency and the Innovative Capability of Firms" *Technology Analysis & Strategic Management*, 16(3): 367–379.
- Tsai W. (2001) "Knowledge transfer in intraorganizational networks: Effects of network position and absorptive capacity on business unit innovation and performance" *Academy of Management Journal*, 44(5): 996–1004.
- Tukey J. W. (1960) "A survey of sampling from contaminated distributions" In Olkin I., Ghurye J.G., Hoeffding W., Madow W.G. and Mann H. (Eds.) *Contributions to Probability and Statistics*. Stanford University Press, Stanford, California: 448–485.
- Tushman M. L. and O'Reilly III C. A. (1996) "Ambidexterous organizations: Managing evolutionary and revolutionary change" *California Management Review*, 38(4): 8–30.
- Uotila J., Maula M., Keil T. and Zahra S. (2009) "Exploration, exploitation, and financial performance: Analysis of S&P 500 corporations" *Strategic Management Journal*, 30(2): 221–231.
- Utterback J.M. (1974) "Innovation in industry and the diffusion of technology" *Science*, 183: 620–626.
- Van de Ven A. H. and Huber G. P. (1990) "Longitudinal field research methods for studying processes of organizational change" *Organization Science*, 1(3): 213–219.
- Van de Ven A. H. and Rogers E. M. (1988) "Innovations and organizations critical perspectives" *Communication Research*, 15(5): 632–651.
- Vandervert L. (1988) "Operational definitions made simple, useful, and lasting" In Ware M. and Brewer C. (Eds.) *Handbook for Teaching Statistics and Research Methods*. Lawrence Erlbaum Associates: Hillsdale, NJ, US: 132–134.

- Verhees F.J.H.M. and Meulenbergh M.T.G. (2004) "Market orientation, innovativeness, product innovation, and performance in small firms" *Journal of Small Business Management*, 42(2): 134–154.
- Verma V., Sharma D. and Sheth J. (2015) "Does relationship marketing matter in online retailing? A meta-analytic approach" *Journal of the Academy of Marketing Science*, DOI 10.1007/s11747-015-0429-6.
- Verona G. (1999) "A resource-based view of product development" *Academy of Management Review*, 24(1): 132–142.
- Vincent L.H., Bharadwaj S.G. and Challagalla G.N. (2004) "Meta-analytic review of antecedents and consequences of innovation" *American Marketing Association Conference Proceedings*, 14: 12–13.
- Viswesvaran C. and Ones D. S. (1995) "Theory testing: Combining psychometric meta-analysis and structural equations modelling" *Personnel Psychology*, 48: 865–885.
- Vogel R. and Güttel W.H. (2013) "The dynamic capability view in strategic management: A bibliometric review" *International Journal of Management Reviews*, 15: 426–446.
- *Vorhies D. and Morgan N. (2005) "Benchmarking marketing capabilities for sustainable competitive advantage" *Journal of Marketing*, 69(1): 80–94.
- Voss G. B., Sirdeshmukh D. and Voss Z. G. (2008) "The effects of slack resources and environmental threat on product exploration and exploitation" *Academy of Management Journal*, 51(1): 147–164.
- Voss G.B. and Voss Z.B. (2000) "Strategic orientation and firm performance in an artistic environment" *Journal of Marketing*, 64(1): 67–83.
- Wang C. L. and Ahmed P. K. (2007) "Dynamic capabilities: A review and research agenda" *International Journal of Management Reviews*, 9(1): 31–51.
- Wang C. L., Senaratne C. and Rafiq M. (2015) "Success traps, dynamic capabilities and firm performance" *British Journal of Management*, 26(1): 26–44.
- Ware J. H. (1985) "Linear models for the analysis of longitudinal studies" *The American Statistician*, 39(2): 95–101.
- Weerawardena J. (2003) "The role of marketing capability in innovation-based competitive strategy" *Journal of Strategic Marketing*, 11(1): 15–35.
- Weerawardena J. and Mavondo F. T. (2011) "Capabilities, innovation and competitive advantage" *Industrial Marketing Management*, 40(8): 1220–1223.

- Weerawardena J. and O'Cass A. (2004) "Exploring the characteristics of the market-driven firms and antecedents to sustained competitive advantage" *Industrial Marketing Management*, 33: 419–428.
- Whetzel D.L. and McDaniel M. A. (1988) "Reliability of validity generalization data bases" *Psychological Reports*, 63(1): 131–134.
- Wilhelm H., Schlömer M. and Maurer I. (2015) "How dynamic capabilities affect the effectiveness and efficiency of operating routines under high and low levels of environmental dynamism" *British Journal of Management*. DOI: 10.1111/1467-8551.12085.
- Williamson O. E. (1999) "Strategy research: governance and competence perspectives" *Strategic Management Journal*, 20(12): 1087–1108.
- Winter S. G. (2003) "Understanding dynamic capabilities" *Strategic Management Journal*, 24: 991–995.
- Wolfe R.A. (1994) "Organizational innovation: Review, critique and suggested research directions" *Journal of Management Studies*, 31 (3): 405–31.
- Wolff M.F. (2007) "Forget R&D spending - think innovation" *Research Technology Management*, 50 (2): 7–9.
- *Wolff J. A. and Pett T. L. (2006) "Small-firm performance: Modeling the role of product and process improvements" *Journal of Small Business Management*, 44(2): 268–284.
- Wong H. and Merrilees B. (2005) "A brand oriented typology for SME: A case research approach" *Journal of Product and Brand Management*, 14(3): 155–162.
- Wong H. and Merrilees B. (2008) "The performance benefits of being brand-orientated" *Journal of Product and Brand Management*, 17(6): 372–383.
- *Yalcinkaya G., Calantone R. J. and Griffith D. A. (2007) "An examination of exploration and exploitation capabilities: Implications for product innovation and market performance" *Journal of International Marketing*, 15(4): 63–93.
- *Yam R., Guan J. C., Pun K. F. and Tang E. P. (2004) "An audit of technological innovation capabilities in Chinese firms: Some empirical findings in Beijing, China" *Research Policy*, 33(8): 1123–1140.
- *Yam R., Lo W., Tang E. P. and Lau A. K. (2011) "Analysis of sources of innovation, technological innovation capabilities, and performance: An empirical study of Hong Kong manufacturing industries" *Research Policy*, 40(3): 391–402.
- Young S. and Tavares A.T. (2004) "Centralization and autonomy: Back to the future" *International Business Review*, 13: 215–237.
- Zablah A. R., Franke G. R., Brown T. J. and Bartholomew D. E. (2012) "How and when does customer orientation influence frontline employee job outcomes? A meta-analytic evaluation" *Journal of Marketing*, 76(3): 21–40.

- *Zahra S. A. and Bogner W. C. (2000) "Technology strategy and software new ventures' performance: Exploring the moderating effect of the competitive environment" *Journal of Business Venturing*, 15(2): 135–173.
- *Zahra S.A and Covin J.G. (1993) "Business strategy, technology policy and firm performance" *Strategic Management Journal*, 14(6): 451–478.
- Zahra S.A and George G. (2002a) "Absorptive capacity: A review, reconceptualization and extension" *Academy of Management Review*, 27(2): 213–40.
- Zahra S.A, Sapienza H.J. and Davidsson P. (2006) "Entrepreneurship and dynamic capabilities: A review, model and research agenda" *Journal of Management Studies*, 43(4): 917–955.
- Zairi M. (1998) *Benchmarking for Best Practice*. Butterworth-Heinem: Oxford, UK.
- Zeithaml V. A., Bitner M. J. and Gremler D. D. (2006) *Services Marketing: Integrating Customer Focus Across The Firm* (4th ed). McGraw Hill: New York.
- Zhang J. A., Garrett-Jones S. and Szeto R. (2013) "Innovation capability and market performance: The moderating effect of industry dynamism" *International Journal of Innovation Management*, 17(02): 1–35.
- Zheng S., Zhang W., Wu X. and Du J. (2011) "Knowledge-based dynamic capabilities and innovation in networked environments" *Journal of Knowledge Management*, 15(6): 1035–1051.
- Zieffler A., Garfield J., Delmas R. and Reading C. (2008) "A framework to support research on informal inferential reasoning" *Statistics Education Research Journal*, 7(2): 40–58.
- Zollo M. and Winter S. (2002) "Deliberate learning and the evolution of dynamic capabilities" *Organizational Science*, 13: 339–351.

Note: Studies incorporated in the PIC–firm performance meta-analysis are marked with an Asterisk (*) preceding their citation.

Appendix-1

Glossary of acronyms/abbreviations (in alphabetical order)

<i>Acronym/Abbreviation</i>	<i>Extended (full) Term</i>
CI	Confidence Interval
CMA	Comprehensive Meta-Analysis
DC	Dynamic Capability/Capabilities
FE	Fixed-Effects
FSD	Firm size Distribution
PIC	Product Innovation Capability
RBV	Resource-Based View
R&D	Research and Development
RE	Random-Effects
SME	Small and Medium Enterprises

Appendix-2

Study Coding Protocol

Constructs of interest:

- a-) Product Innovation Capability
b-) Firm performance

1. Study descriptors

1.1. General study specifications

1 2 3

- a) Study reference number: _____
- b) Study type: ☐ Conference paper/proceedings ☐ Scholarly journal article
- c) Study characteristics:

<i>Study Context</i>	<i>Yes / No</i>	<i>Description</i>
Industry specific		
Market/country specific		

Search method: ☐ Electronic (Online database search) ☐ Manual

1.2. Citation Information

4 5 6 7 8 9 10 11

First authors last name (First eight letters): _____

Title: _____

Publication: _____ Year Pub: _____

If unpublished, details: _____

1.3. Study research design

	<i>Incorporation criteria</i>	<i>Yes</i>	<i>No</i>	<i>Comments</i>
1.	Is the study empirical? Does the study provide evidence of verifiable, observational data			
2.	Does the study report effect size for the constructs and relationship of interest?			
3.	Does the study report sample size and investigates independent samples?			

Sample size/sub-sample size: _____ Independent samples: Yes / No

Sample/ sub-sample size, Cronbach's Alpha, Average firm size mentioned on study page number: _____

Sampling procedure: _____

Does the study satisfy incorporation criteria (described above): Yes / No

2. Empirical findings of the study

2.1. Effect size and related statistics

<i>Effect size</i>	<i>Value</i>	<i>Comments</i>	<i>Study page no.</i>
Correlation coefficient (r) / Others (F, t, χ^2 etc)			
Inverse variance weight			
Other statistics (e.g., standard deviation, variance, etc.)			
Artifacts (for disattenuation)			
Computation procedure			
<i>Moderator variables (if reported/identified)</i>	<i>Labels / Names</i>	<i>Values</i>	<i>Study page no.</i>
Variables			
Magnitude of moderation effects			
<i>Mediators (if reported/identified)</i>			

2.2. Miscellaneous comments/Additional information

Appendix-3

Meta-analytic reviews (in alphabetical order) and their study numbers

S. No.	Meta-analytic reviews (Author, Year)	No. of incorporated studies
1	Balkundi and Harrison (2006)	17 studies
2	Bowen et al. (2010)	55 studies
3	Brinckmann et al. (2010)	46 studies
4	Camisón-Zornoza et al. (2004)	53 studies
5	Cohen (1993)	34 studies
6	Crook et al. (2011)	66 studies
7	Damanpour (1991)	46 studies
8	Damanpour (1992)	20 studies
9	Greenley (1995)	46 studies
10	Harrison et al. (2006)	24 studies
11	Joshi and Roh (2009)	39 studies
12	Kellermanns et al. (2011)	21 studies
13	Ketchen et al. (1997)	33 studies
14	Leuschner et al. (2013)	39 studies
15	Li and Cropanzano (2009)	12 studies
16	Liang et al. (2010)	50 studies
17	Miller et al. (1991)	31 studies
18	McEvoy and Cascio (1987)	24 studies
19	Phillips (1998)	40 studies
20	Read et al. (2009)	48 studies
21	Rosenbusch et al. (2011)	42 studies
22	Sarooghi et al. (2015)	52 studies
23	Sivasubramaniam et al. (2012)	38 studies
24	Stam et al. (2014)	59 studies

Appendix-4

Screenshot of CMA-generated table containing basis statistics

The screenshot displays the 'Comprehensive meta analysis - [Analysis]' window. The main table shows basis statistics for two models: Fixed and Random. The table includes columns for Model, Number Studies, Point estimate, Lower limit, Upper limit, Z-value, P-value, Q-value, df (Q), P-value, I-squared, Tau Squared, Standard Error, Variance, and Tau.

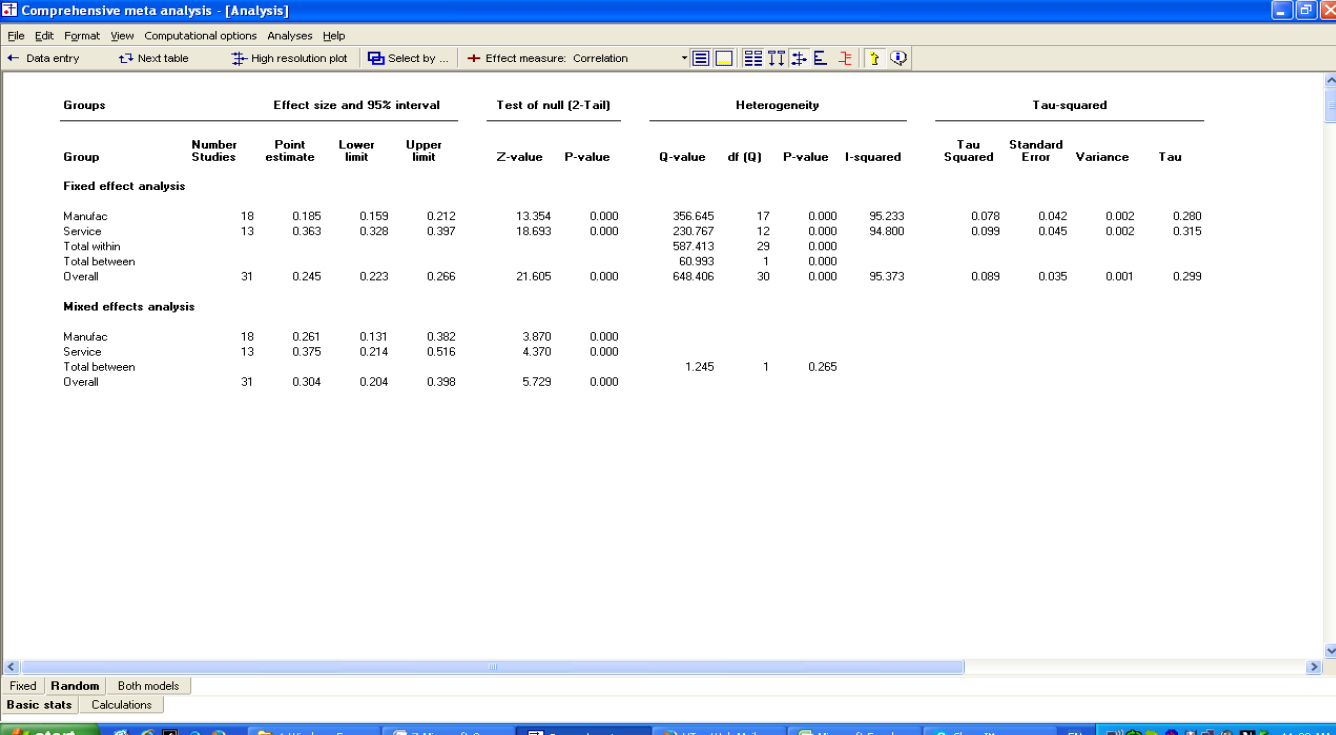
Model	Number Studies	Effect size and 95% interval			Test of null (2-Tail)		Heterogeneity				Tau-squared			
		Point estimate	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed	58	0.342	0.327	0.356	41.702	0.000	1377.977	57	0.000	95.864	0.099	0.026	0.001	0.315
Random	58	0.379	0.305	0.448	9.331	0.000								

At the bottom of the window, there are tabs for 'Fixed', 'Random', and 'Both models'. Below these are 'Basic stats', 'One study removed', 'Cumulative analysis', and 'Calculations'. The Windows taskbar at the bottom shows the start button, several open applications, and the system clock indicating 11:35 PM.

Appendix-5

Screenshots of moderation tables

5.a. Industry type



Comprehensive meta analysis - [Analysis]

File Edit Format View Computational options Analyses Help

← Data entry → Next table → High resolution plot → Select by ... → Effect measure: Correlation

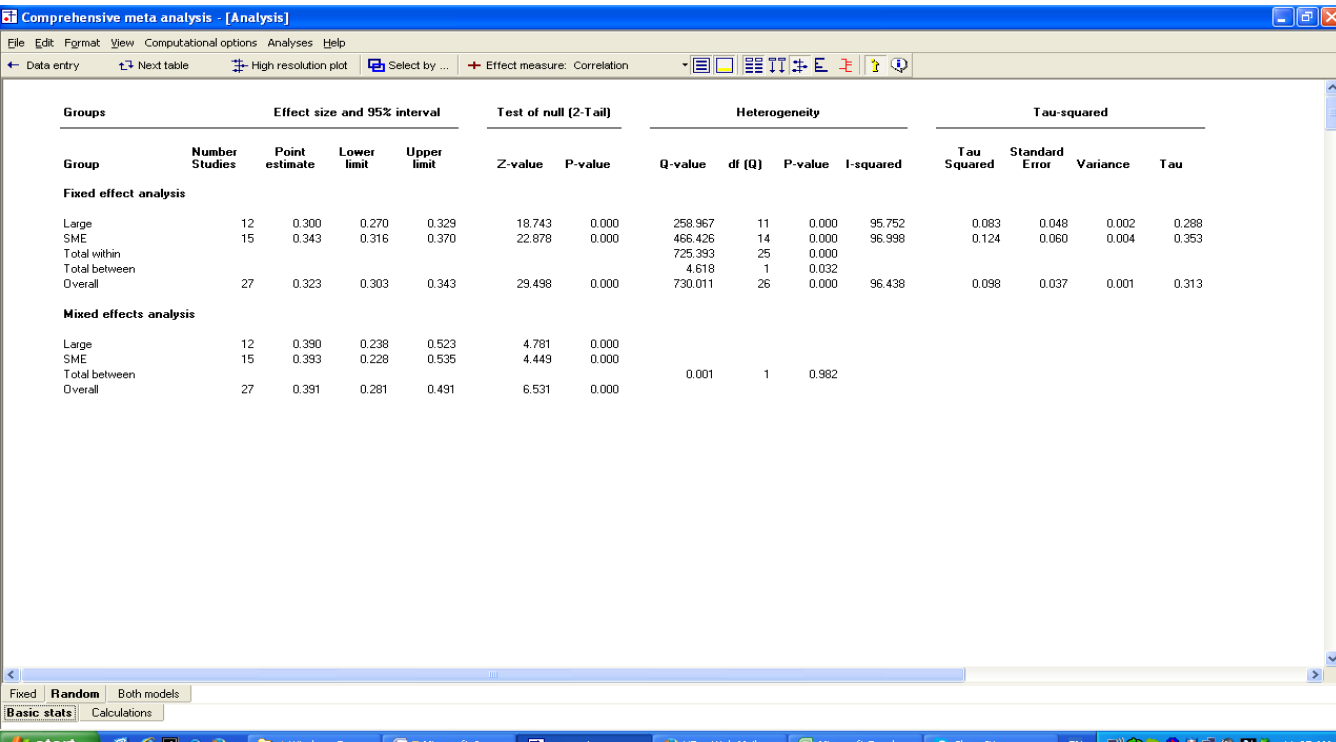
Groups		Effect size and 95% interval			Test of null (2-Tail)		Heterogeneity				Tau-squared			
Group	Number Studies	Point estimate	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed effect analysis														
Manufac	18	0.185	0.159	0.212	13.354	0.000	356.645	17	0.000	95.233	0.078	0.042	0.002	0.280
Service	13	0.363	0.328	0.397	18.693	0.000	230.767	12	0.000	94.800	0.099	0.045	0.002	0.315
Total within							587.413	29	0.000					
Total between							60.993	1	0.000					
Overall	31	0.245	0.223	0.266	21.605	0.000	648.406	30	0.000	95.373	0.089	0.035	0.001	0.299
Mixed effects analysis														
Manufac	18	0.261	0.131	0.382	3.870	0.000								
Service	13	0.375	0.214	0.516	4.370	0.000								
Total between							1.245	1	0.265					
Overall	31	0.304	0.204	0.398	5.729	0.000								

Fixed Random Both models

Basic stats Calculations

start Windows E... 7 Microsoft O... Comprehensive... Ufas Web Mail ... Microsoft Excel... Skype™ - sum... EN 11:32 AM

5.b. Firm size



Comprehensive meta analysis - [Analysis]

File Edit Format View Computational options Analyses Help

← Data entry → Next table → High resolution plot → Select by ... → Effect measure: Correlation

Groups		Effect size and 95% interval			Test of null (2-Tail)		Heterogeneity				Tau-squared			
Group	Number Studies	Point estimate	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed effect analysis														
Large	12	0.300	0.270	0.329	19.743	0.000	258.967	11	0.000	95.752	0.083	0.048	0.002	0.288
SME	15	0.343	0.316	0.370	22.878	0.000	466.426	14	0.000	96.998	0.124	0.060	0.004	0.353
Total within							725.393	25	0.000					
Total between							4.618	1	0.032					
Overall	27	0.323	0.303	0.343	29.498	0.000	730.011	26	0.000	96.438	0.098	0.037	0.001	0.313
Mixed effects analysis														
Large	12	0.390	0.238	0.523	4.781	0.000								
SME	15	0.393	0.228	0.535	4.449	0.000								
Total between							0.001	1	0.982					
Overall	27	0.391	0.281	0.491	6.531	0.000								

Fixed Random Both models

Basic stats Calculations

start Windows E... 7 Microsoft O... Comprehensive... Ufas Web Mail ... Microsoft Excel... Skype™ - sum... EN 11:35 AM

5.c. Technological turbulence

Comprehensive meta analysis - [Analysis]														
File Edit Format View Computational options Analyses Help														
Data entry Next table High resolution plot Select by ... Effect measure: Correlation														
Groups		Effect size and 95% interval			Test of null (2-Tail)		Heterogeneity				Tau-squared			
Group	Number Studies	Point estimate	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed effect analysis														
High	36	0.306	0.288	0.324	30.578	0.000	945.996	35	0.000	96.300	0.103	0.035	0.001	0.321
Low	9	0.331	0.295	0.366	16.893	0.000	62.496	8	0.000	87.199	0.027	0.017	0.000	0.163
Total within							1008.493	43	0.000					
Total between							1.444	1	0.230					
Overall	45	0.311	0.295	0.327	34.913	0.000	1009.936	44	0.000	95.643	0.086	0.025	0.001	0.293
Mixed effects analysis														
High	36	0.340	0.241	0.432	6.416	0.000								
Low	9	0.336	0.231	0.434	5.959	0.000								
Total between							0.003	1	0.955					
Overall	45	0.338	0.267	0.406	8.756	0.000								

Fixed **Random** Both models

Basic stats Calculations

Appendix-6

Adjustment factors for the incorporated studies

Study name (Author, year)	Average firm size (Raw data)	Average firm size (log transformations, as used for calculations)	Weights= Average firm size/Mean (Mean=2.2)	Adjustment Factors= (Weights) ^{1/2}
Akgün et al (2009)	186.2	2.269979677	1.031808944	1.015779968
Ar and Baki (2011)	9.5	0.977723605	0.444419821	0.666648199
Artz et al (2010)	631	2.800029359	1.272740618	1.128158064
Baer and Frese (2003)	327	2.514547753	1.142976251	1.069100674
Calantone et al (2002)	103.5	2.01494035	0.915881977	0.957017229
Chen et al (2009)	103.5	2.01494035	0.915881977	0.957017229
Chen, Tsou and Huang(2009)	103.5	2.01494035	0.915881977	0.957017229
Coombs and Bierly (2006)	103.5	2.01494035	0.915881977	0.957017229
Correa et al (2007)	2511.89	3.400000617	1.545454826	1.243163234
Craig and Dibrell (2006)	1.93	0.285557309	0.129798777	0.360275973
Cui et al (2005)	1075	3.031408464	1.377912938	1.173845364
Dai and Liu (2009)	50.21	1.700790221	0.773086464	0.879253356
Deeds et al (1998)	66	1.819543936	0.827065425	0.909431375
Dibrell et al (2008)	34.5	1.537819095	0.69900868	0.836067389
Eisingerich et al (2009)	103.5	2.01494035	0.915881977	0.957017229
Ettlie and Pavlou (2006)	63000	4.799340549	2.181518432	1.476996422
Garcia-Morales et al (2007)	103.5	2.01494035	0.915881977	0.957017229
Garg et al (2003)	80	1.903089987	0.865040903	0.930075751
Gopalakrishnan (2000)	103.5	2.01494035	0.915881977	0.957017229
Grawe et al (2009)	928	2.967547976	1.348885444	1.161415276
Guan and Ma (2003)	1072	3.030194785	1.377361266	1.173610355
Heeley et al (2007)	103.5	2.01494035	0.915881977	0.957017229
Heunks (1998)	49.6	1.695481676	0.770673489	0.877880111
Hult et al (2004)	103.5	2.01494035	0.915881977	0.957017229

Jansen et al (2006)	33.37	1.523356207	0.692434639	0.832126577
Jimenez and Valle (2011)	103.5	2.01494035	0.915881977	0.957017229
Kalafsky and MacPherson (2002)	60	1.77815125	0.808250568	0.899027568
Katila and Ahuja (2002)	39000	4.591064607	2.086847549	1.44459252
Kim et al (2011)	103.5	2.01494035	0.915881977	0.957017229
Kuckertz et al (2010)	31.47	1.497896743	0.680862156	0.825143718
Lawson et al (2012)	1318.257	3.12	1.418181818	1.19087
Lee et al (2001)	30.6	1.485721426	0.675327921	0.821783378
Li and Atuahene-Gima (2001)	161	2.206825876	1.003102671	1.001550134
Lin and Chen (2008)	1632	3.212720154	1.460327343	1.208440045
Löf and Heshmati (2006)-Sample A	46.47	1.667172672	0.75780576	0.870520396
Löf and Heshmati (2006)-Sample B	46.47	1.667172672	0.75780576	0.870520396
Luo et al (2005)	103.5	2.01494035	0.915881977	0.957017229
Mithas et al (2011)	103.5	2.01494035	0.915881977	0.957017229
O'Cass and Sok (2012)	71.88	1.856608068	0.843912758	0.918647244
O'Cass and Sok (2013)	29.92	1.475961589	0.670891631	0.819079747
Panayides (2006)	49.7	1.696356389	0.771071086	0.878106534
Penner-Hahn and Shaver (2005)	103.5	2.01494035	0.915881977	0.957017229
Rhodes et al (2008)	103.5	2.01494035	0.915881977	0.957017229
Richard et al (2003)	127	2.103803721	0.956274419	0.977892846
Richard et al (2004)	154	2.187520721	0.9943276	0.997159767
Salomo et al (2008)	29486	4.469615861	2.031643573	1.425357349
Schoenecker and Swanson (2002)	103.5	2.01494035	0.915881977	0.957017229
Schilke (2014)	1778.28	3.25	1.4773	1.215
Sirén et al (2012)	171.34	2.233858763	1.015390347	1.007665791
Tatikonda and Montoya-Weiss (2001)	103.5	2.01494035	0.915881977	0.957017229
Thornhill (2006)	24.41	1.387567779	0.630712627	0.794174179
Vorhies and Morgan (2005)	391	2.592176757	1.178262162	1.08547785
Wolff and Pett (2006)	103.5	2.01494035	0.915881977	0.957017229
Yalcinkaya et al (2007)	58	1.763427994	0.801558179	0.895297816
Yam et al (2004)	103.5	2.01494035	0.915881977	0.957017229
Yam et al (2011)	1380	3.139879086	1.427217767	1.194662198
Zahra and Bogner (2000)	47.19	1.673849977	0.760840899	0.872261944
Zahra and Covin (1993)	103.5	2.01494035	0.915881977	0.957017229

